The Extent of Adverse Selection on Risk Management of Rural Energy Projects in Tanzania

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Abstract

This study explored how adverse selection affects risk management in rural energy projects in Tanzania, using insights from Information Asymmetry Theory and the Dynamic Capabilities View. The findings show that when gaps in information are reduced, collaboration among stakeholders improves, supporting better decisions and contributing to more sustainable project performance. A quantitative cross-sectional approach was used, involving 175 project managers, and the analysis was carried out through Partial Least Squares Structural Equation Modeling (PLS-SEM). The results suggest that engaging stakeholders and incorporating local knowledge contribute more strongly to project success than addressing information asymmetry alone. Clear communication and openness help reduce misunderstandings, while adaptive capabilities enable project teams to respond to unpredictable rural environments and limited resources. Integrating community knowledge into planning and implementation also strengthens the relevance of risk management strategies and improves the flexibility needed to handle social, cultural, and economic challenges on the ground. Overall, the study highlights that effective rural energy projects require both transparent information-sharing and adaptive management practices. Encouraging participation and building organizational capabilities allow projects to better manage risks, remain aligned with local realities, and enhance long-term sustainability. The study adds to existing literature by showing that risk management in rural contexts is most effective when it is transparent, inclusive, and responsive to changing conditions.

Keywords: Adverse selection, Risk management, Rural energy projects, Stakeholder engagement, Information asymmetry, Local knowledge integration

Introduction

Rural energy projects play a central role in improving electricity access and supporting economic and social development in underserved areas. Despite their importance, many of these projects face setbacks linked to adverse selection. In this study, adverse selection refers to situations where key actors such as funders, implementing agencies, or community representatives make decisions without having a clear or complete understanding of local realities, stakeholder capabilities, or hidden project risks. As noted by Owusu-Manu et al. (2021), such mismatches in pre-project information often lead to choices that are inefficient or poorly suited to the context. Unlike the broader idea of information asymmetry, which can occur

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at any stage of a project, the emphasis here is on the decisions made before contracts are signed, including the selection of contractors, technologies, and financing arrangements. To analyze adverse selection in rural energy development, the study draws on several practical indicators. These include: differences between what stakeholders expect and what is eventually delivered; hiring or partnering with actors who later prove to lack the technical or managerial capacity required; financial challenges such as unplanned costs that arise because important risks were not identified early enough; and low levels of community uptake or satisfaction with the energy solutions provided. Limited use of local insights such as cultural norms, community priorities, or environmental conditions also serves as a sign that adverse selection may be present during planning or implementation.

Recognizing and understanding how adverse selection emerges is essential for improving the quality, results, and long-term viability of rural energy efforts. Tanzania, where energy access remains uneven across regions, provides a suitable context for examining how information gaps influence project performance. By defining adverse selection clearly and linking it to observable outcomes, this study offers a structured way to investigate its role in rural energy initiatives. It also provides direction for improving risk management, strengthening collaboration among stakeholders, and enhancing the sustainability of future energy interventions.

Risk Management Effectiveness in the Rural Energy Project

Reliable energy access remains one of the foundations of social and economic progress. Even with global improvements, hundreds of millions of people particularly those living in remote areas still lack electricity (IEA, 2022). Rural electrification, therefore, depends not only on technological and financial investment but also on the ability of project teams to manage risks that arise during planning and implementation. One of the most persistent challenges is adverse selection, which stems from uneven access to information and often leads to design flaws or poor implementation decisions. Economic scholars such as Stiglitz (1976) and Hellwig (1987) long ago established how incomplete information distorts choices made by contracting parties. Later work by Borenstein and Davis (2012) showed how these dynamics also influence the energy sector by affecting investment behaviour, pricing, and consumer uptake. These challenges are intensified in rural settings, where government institutions, private companies, and communities often operate with different levels of insight into local realities. As a result, expectations clash, and energy projects may be introduced without a proper understanding of community needs or constraints.

Experiences from Sub-Saharan Africa illustrate how different countries attempt to manage these risks. Kenya, for example, has seen relatively stable outcomes from private off-grid solar providers, which tend to rely on clearer contractual arrangements and stronger accountability mechanisms (Boliko, 2020). Field experiments on connection subsidies showed that while full subsidies increased uptake, partial or no subsidies had far weaker results because households still faced barriers like credit limitations, slow administrative procedures, or unreliable service delivery (Lee, 2023; Lee et al., 2020). Other research (Avedi, 2020; Sanka, 2024) points to the importance of careful planning, adequate funding, and consistent monitoring. Together, these studies demonstrate that risk management improves when financial structures, institutional oversight, and private-sector involvement work together to reduce information gaps. Tanzania's situation reflects a different pattern. Although electrification efforts have expanded in recent years, access in rural communities remains low estimated at around 40 percent (World Bank, 2022). Many projects struggle with long-term financial viability and limited community participation. Research indicates that differences in the type and quality of information held by project actors contribute to unrealistic assumptions, weak coordination, and interventions that fall short of local needs (Chuwa & Perfect-Mrema, 2025). Unlike settings where subsidies and strong regulatory systems cushion these challenges, Tanzania faces more fundamental problems linked to persistent information imbalances and the resulting adverse selection.

Other countries in the region have adopted a wide range of policy strategies from subsidized connections to public-private partnerships to broaden electricity access (Owusu-Manu et al., 2021). While these approaches have produced notable progress in countries such as Ethiopia, Rwanda, and Kenya, ongoing issues around affordability, reliability, and sustainability remain (World Bank, 2022; Lee et al., 2020). Tanzania stands out because the underlying obstacles are less about infrastructure or funding and more about the difficulty of aligning project actors who possess different levels of knowledge about local conditions. Improving rural energy outcomes, therefore, requires more than technical fixes. As Twesigye (2021) observes, stronger attention must be paid to risk management approaches that emphasize transparency, regular communication, and the inclusion of local perspectives. Ensuring that communities and implementers share accurate information can reduce the likelihood of misinformed decisions and help projects reflect actual needs. Unlike neighbouring countries that rely heavily on subsidies or regulatory reforms, Tanzania needs strategies that build trust, support openness, and encourage collaboration among stakeholders if rural energy initiatives are to achieve meaningful and lasting results.

Theoretical Perspectives

Information Asymmetry Theory

Information Asymmetry Theory helps explain why rural energy projects often struggle with coordination and decision-making. Stakeholders involved in these projects government bodies, financiers, technical experts, and community representatives rarely begin with the same level or type of information. Implementers may have strong technical expertise but little understanding of local social dynamics or environmental conditions. In contrast, communities may be familiar with their needs and constraints but lack detailed knowledge about technologies or financing models. This imbalance contributes to what this study refers to as information asymmetry and has been noted in recent work such as Menyeh and Acheampong (2024). Scholars have pointed out, however, that information asymmetry is not always entirely negative. Screening and monitoring tools can reduce information gaps, and in certain contexts, asymmetry may even open space for experimentation and entrepreneurial initiative (Pernagallo, 2024). These critiques suggest that improving information flows should not be limited to increasing transparency. Effective engagement must also recognize the value of local insights, treating them as critical inputs rather than shortcomings that need correction.

Dynamic Capabilities Framework

The Dynamic Capabilities Framework focuses on an organization's ability to adjust its resources, routines, and strategies in order to remain effective in changing conditions (Teece et al., 2016). This viewpoint is particularly relevant to rural energy initiatives in Tanzania, where implementers must navigate unpredictable weather, evolving policies, and diverse community priorities. The framework highlights how learning, reconfiguring resources, and continuous adjustment play a role in sustaining project performance in such environments. Despite its usefulness, the framework has been criticized. Some authors argue that the concept lacks clear boundaries, making it difficult to measure or apply consistently (Wenzel et al., 2021). Others note that dynamic capabilities often seem to be identified only after a project succeeds, which raises questions about their predictive value. Debates also persist regarding whether dynamic capabilities are best understood as routines, higher-level skills, or something in between (Tian et al., 2023). Even with these limitations, the framework offers a helpful lens for examining how project teams adapt, innovate, and respond to the uncertainties inherent in rural development work.

Empirical Review and Development of Hypotheses

The effectiveness of risk management in rural energy projects is strongly shaped by the quality of information available to project stakeholders. Across the literature, adverse selection is consistently identified as a core challenge arising from information asymmetries between governments, financiers, developers, and local communities. Weak data quality limits the ability of decision-makers to accurately assess project risks, allocate resources efficiently, and design context-appropriate interventions. At the global level, evidence shows that inadequate or unevenly distributed information increases economic and political risks, particularly in renewable energy investments operating in uncertain policy environments (Chebotareva et al., 2020; Kul et al., 2020). These studies collectively emphasize that when stakeholders rely on incomplete or unreliable data, investment decisions become distorted, leading to heightened uncertainty and suboptimal project outcomes. Beyond investment decisions, data inequality also affects how risks are perceived and managed throughout the project lifecycle. Leonard et al. (2022) demonstrate that poor data transparency can lead to misaligned expectations among stakeholders, contributing to ineffective implementation and adverse social and environmental outcomes. Their framework highlights that data quality is not merely a technical concern but a governance issue that influences accountability, coordination, and trust. In developing-country contexts, where institutional capacity may be limited, these challenges are often magnified. Evidence from Tanzania further illustrates how information gaps shape organizational outcomes. Kambi and Kasoga (2024) show that firms facing higher information asymmetry incur unfavorable financing conditions, which negatively affect performance. Although their study focuses on SMEs, the findings are highly relevant to rural energy projects, where similar informational imbalances between funders and implementers can undermine risk management effectiveness.

Despite broad recognition of adverse selection in renewable energy literature, existing studies largely emphasize policy frameworks and financial risks while offering limited empirical insight into how data quality directly shapes risk management outcomes in rural energy projects. Moreover, few studies explicitly examine how contextual factors such as gender dynamics, cultural norms, and community structures interact with data availability to influence project performance. Research suggests that access to reliable information can alter intra-household and community decision-making, particularly by enabling women's participation and improving time allocation (Leduchowicz-Municio et al., 2023). However, without gender-sensitive data systems, these potential benefits may remain unevenly distributed. Similarly, cultural norms and trust networks shape how information is interpreted and acted upon in rural settings (Osobajo et al., 2023; Delea et al., 2024). These insights point to a critical gap in understanding the role of data quality as a foundational determinant of risk management effectiveness in rural energy initiatives.

H1: Data quality positively influences the effectiveness of rural energy project outcomes.

Stakeholder Engagement and Risk Management Effectiveness

Stakeholder engagement has emerged as a central mechanism through which complex risks in renewable energy projects can be identified, communicated, and managed. The literature converges on the view that rural energy projects involve interdependent technical, economic, social, and political risks that cannot be effectively addressed without inclusive engagement processes. Abba et al. (2022) emphasize that understanding interactions among multiple risk drivers requires active participation from diverse stakeholders, particularly in developing-country contexts where local conditions vary widely. Their multidimensional risk framework underscores that stakeholder engagement enhances risk identification and supports evidence-based decision-making. At the organizational level, stakeholder engagement also shapes institutional culture and collective responsibility. Salvioni and Almici (2020) argue that effective engagement fosters shared values aligned with sustainability, thereby strengthening long-term commitment to project goals. This perspective aligns with empirical evidence from Malik et al. (2023), who demonstrate that communication quality significantly enhances stakeholder engagement, which in turn improves project success. Their findings suggest that engagement operates not only as a participatory mechanism but also as a conduit through which information flows, feedback is generated, and adaptive risk responses are developed.

Evidence from Tanzania reinforces the contextual relevance of stakeholder engagement for project effectiveness. Sanka (2024) shows that donor-funded projects with strong community participation and alignment to local priorities achieve higher sustainability and impact. Although focused on WASH initiatives, these findings are directly transferable to rural energy projects, where community ownership and trust are essential for managing implementation and operational risks. Nevertheless, despite extensive discussion of stakeholder engagement across sectors, the literature offers limited empirical examination of how engagement systematically enhances risk management practices specifically in rural energy projects. This gap underscores the need to empirically test the contribution of stakeholder engagement to rural energy project outcomes.

H2: Enhanced stakeholder engagement positively influences rural energy project outcomes.

Integration of Local Knowledge and Risk Management in Rural Energy Projects

The integration of local knowledge has gained increasing attention as a means of improving resilience, adaptability, and sustainability in rural development initiatives. Across climate adaptation and energy transition literature, local knowledge is recognized as a critical resource that complements technical expertise by embedding projects within social, environmental, and cultural realities. Filho et al. (2023) show that communities in the Global South rely on indigenous knowledge systems to anticipate environmental risks, yet these insights are frequently excluded from formal policy and planning processes. This exclusion increases vulnerability and weakens adaptive capacity.

In renewable energy contexts, similar patterns emerge. Wang et al. (2023) demonstrate that local perceptions and peer effects significantly influence the adoption of photovoltaic technologies, highlighting the cognitive and social dimensions of energy transitions. Omole et al. (2024) further emphasize that socio-cultural dynamics shape the sustainability of rural electrification initiatives, suggesting that failure to integrate local knowledge can lead to resistance, misuse, or abandonment of energy systems. Methodological contributions by Janota et al. (2023) and Yu and Mu (2023) reinforce the importance of context-specific approaches, arguing that localized knowledge is essential for overcoming economic, geographic, and institutional barriers to energy implementation. Despite this growing recognition, the literature remains fragmented regarding the direct role of local knowledge in enhancing risk management effectiveness in rural energy projects. Most studies focus on resilience, adaptation, or adoption outcomes, rather than explicitly linking local knowledge integration to systematic risk mitigation. This gap is particularly salient in rural energy projects, where uncertainty related to environmental conditions, social acceptance, and institutional coordination is high. Addressing this gap is essential for understanding how locally grounded knowledge can strengthen decision-making and improve project outcomes.

H3: The effective integration of local knowledge positively influences rural energy project outcomes.

Conceptual model

This study's conceptual framework explains rural energy project outcomes through three main determinants: data quality, stakeholder engagement, and the use of local knowledge. It proposes that reliable and accurate data improve project effectiveness by guiding decisions and resource use. In addition, strong stakeholder engagement is expected to enhance outcomes by promoting collaboration, trust, and a sense of ownership among participants. The framework also suggests that incorporating local knowledge contributes positively to project results by aligning interventions with community needs and practices.

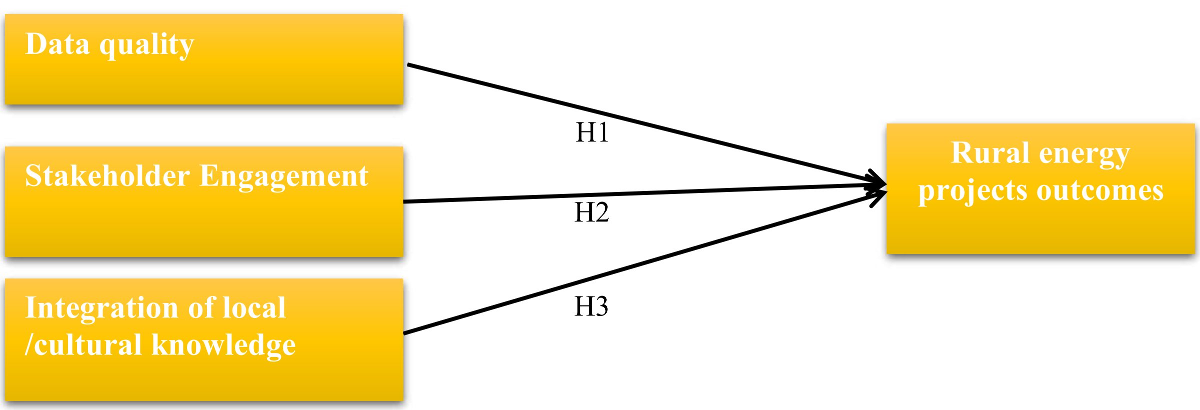

Figure 1: Conceptual framework

Methodology

Research Design and Procedures

This study used a cross-sectional research design, which made it possible to collect information from project managers overseeing REA projects completed in Tanzania in 2023. The choice of this design was driven by practical considerations: it allows researchers to capture views and experiences within a single period, making it suitable for studies with limited time and resources. Project managers were targeted because they are involved in planning, coordination, supervision, and reporting, giving them a clear understanding of how rural energy projects are implemented and the challenges encountered. Alongside the structured questionnaires used for collecting quantitative data, the study also included semi-structured interviews with selected project managers and other actors involved in rural energy delivery. These interviews helped to clarify issues that could not be fully explained through numerical data alone. They provided perspectives on how data quality (DI), stakeholder involvement (SE), and local knowledge (LK) shape project performance. Combining questionnaires and interviews allowed the study to examine both the measurable relationships among variables and the contextual factors that influence project results.

The research focused on individuals directly engaged in rural energy projects completed under REA in 2023. The initial group included 175 project managers, identified from the REA project registry covering the period 2018–2023. These individuals were selected because their positions give them first-hand knowledge of how decisions are made, the quality of information available during implementation, and the interaction between project teams and community members. The sampling frame included both successful and unsuccessful projects. Eligibility was limited to those who held managerial or operational roles such as project managers, local leaders involved in project oversight, and other stakeholders directly connected to implementation or monitoring. Those with temporary or peripheral involvement (e.g., short-term laborers or consultants without site-based duties) were excluded. Records from REA's annual reports helped identify projects that were discontinued or did not progress to operational status. To avoid drawing conclusions based only on successful projects, perspectives were also gathered from managers of discontinued projects and representatives of local communities served by the initiatives. Of the 175 project managers contacted, 142 completed the survey, giving a response rate of 81.1%.

A structured questionnaire was used to gather quantitative data for the study. The instrument was designed to capture information relevant to the study variables and to support the testing of the proposed hypotheses. The development process drew on established questionnaire design principles, ensuring that each item corresponded clearly to the constructs under investigation. All items were measured using a seven-point Likert scale, allowing respondents to express the extent of their agreement or experience with each statement. Quantitative data were selected for their strength in supporting comparisons across respondents and in helping identify general patterns within the studied projects. The questionnaire was distributed to individuals involved in rural energy implementation within the selected project sites. Before administering the main survey, the tool was piloted with 17 projects roughly 10 percent of the intended sample. The pilot helped assess how well the questions captured the intended concepts and whether respondents interpreted the items as expected. The results indicated acceptable levels of convergent validity, with scores of 0.561 for data quality (DI), 0.670 for stakeholder engagement (SE), and 0.726 for the integration of local knowledge (LK). Reliability tests also showed strong internal consistency, with coefficients of 0.848 for DI, 0.930 for SE, and 0.926 for LK. Feedback from the pilot phase led to the revision or removal of items that were unclear, repetitive, or not contributing meaningfully to the analysis.

Once data were collected, they were entered into SPSS (Version 27) for cleaning and screening. Initial checks were conducted to correct entry errors and identify any missing responses or unusual values. Missing data were handled using linear interpolation, which helped preserve the structure of the dataset without introducing major distortions. Visual inspection using boxplots indicated that extreme values were minimal and did not pose a significant threat to the analysis. After preliminary checks, the study employed PLS-SEM to examine the relationships among the core variables. The coefficient of determination (R^2) served as a primary indicator of how well the model explained variations in project outcomes, reflecting the predictive strength of the specified paths.

Results

The analysis was based on data collected from 142 respondents directly involved in the planning, implementation, and oversight of rural energy projects under the Rural Energy Agency (REA), representing an 81.1% response rate from the targeted population. Given that the sample includes managers and stakeholders from both successful and discontinued projects, it provides a sufficiently diverse and informed basis for assessing the measurement properties of the constructs and is therefore appropriate for evaluating the adequacy of the model. A confirmatory factor analysis (PLS-CFA) was performed to determine whether the measurement model adequately represented the data. The evaluation considered individual factor loadings (Figure 2), construct reliability, and the quality of the model's convergent and discriminant validity. Most indicators loaded above the commonly accepted threshold of 0.7, signifying that the items were strongly associated with their corresponding constructs. Composite reliability scores for all constructs were above 0.7, demonstrating satisfactory internal consistency. Cronbach's alpha values also surpassed the 0.7 requirement, reinforcing the reliability of the scales. Convergent validity was confirmed through AVE values above 0.5, indicating that the constructs captured an adequate proportion of variance from their items. Discriminant validity was assessed using the Fornell–Larcker approach, comparing the square root of each construct's AVE with its correlations with other constructs. As summarized in Table 2, the results supported the distinctiveness of all constructs and confirmed that the measurement model was sound.

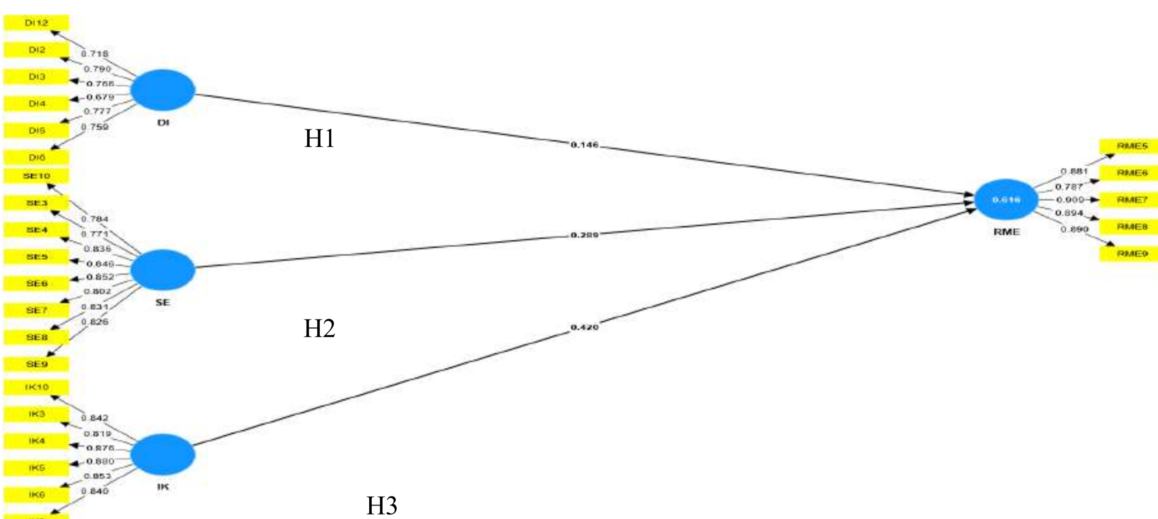

Figure 2: Structural model showing outer loadings, path coefficients and R-square.

The outer loadings (Table 1) show how strongly each indicator reflects its underlying construct, while the path coefficients reveal both the strength and direction of the proposed relationships among the constructs. The R^2 values indicate how much of the variation in the dependent variables is accounted for by the predictors. To test the reliability and significance of these estimates, the study used bootstrap resampling with 5,000 iterations. On the other hand, VIF values test for multicollinearity to confirm the reliability and validity of the measurement model; all thresholds were met.

Table 1: Factor loading for constructs and Variance Inflation Factor (VIF)

Indicator	DI	IK	RME	SE	VIF
DI12	0.718				1.618
DI2	0.790				2.015
DI3	0.766				2.021
DI4	0.679				1.496
DI5	0.777				1.839
DI6	0.759				1.843
IK10		0.842			2.891
IK3		0.819			2.741
IK4		0.876			4.115
IK5		0.880			3.472
IK6		0.853			2.619
IK9		0.840			2.826
RME5			0.881		2.957
RME6			0.787		1.963
RME7			0.909		3.584
RME8			0.894		3.244
RME9			0.890		3.206
SE10				0.784	2.195
SE3				0.771	2.006
SE4				0.836	3.021
SE5				0.846	3.364
SE6				0.852	3.136
SE7				0.802	2.526
SE8				0.831	2.634
SE9				0.826	2.652

Source: Data analysis from field data (2024)

Table 2 presents Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE), where Alpha and CR assess internal consistency, and AVE measures convergent validity of the constructs.

Table 2: Construct reliability and validity

Construct	Cronbach's alpha	Composite reliability	AVE
DI	0.843	0.848	0.561
IK	0.924	0.926	0.726
RME	0.922	0.929	0.762
SE	0.930	0.930	0.670

Source: Data analysis from field data (2024)

Table 2 evaluates the reliability and validity of the constructs. All four constructs (DI, IK, RME, SE) demonstrate adequate internal consistency, with Cronbach's alpha values above 0.70 and composite reliability scores higher than 0.80. The average variance extracted (AVE) also exceeds the minimum requirement of 0.50 for each construct, confirming convergent validity. Table 1 presents the factor loadings of all observed indicators on their respective latent constructs, showing the extent to which each item represents its construct. Factor loadings above 0.7 indicate strong indicator reliability. The Variance Inflation Factor (VIF) values are also provided to assess multicollinearity among indicators, with values below 5 indicating no significant collinearity issues.

Table 3: Discriminant validity using Heterotrait-Monotrait Ratio of Correlations

Construct	DI	IK	SE
DI	0.844		
IK	0.758	0.797	
SE	0.838	0.801	0.764

Source: Data analysis from field data (2024)

Table 4 presents R^2, Q^2, and f^2 values assessing the structural model's quality, showing the variance explained (R^2), predictive relevance (Q^2), and effect size (f^2) of adverse selection on risk management of rural energy projects in Tanzania. Higher R^2 indicates stronger explanatory power, $Q^2 > 0$ indicates good predictive relevance, and f^2 shows the strength of each predictor's contribution.

Table 4: R-square and Q-square to assess the Quality of the structural model

Variable	R^2	Q^2	f^2
RME	0.616	0.485	
DI		0	0.183
IK		0	0.048
SE		0	0.360

Source: Data analysis from field data (2024)

The tables (1 to 4) presented in this study on the extent of adverse selection in rural energy projects implementation in Tanzania provide key details on the validity, reliability, and relationships between the constructs influencing rural electrification projects' outcomes. Table 1 shows the factor loadings for each indicator of the constructs, with all indicators displaying loadings above the recommended threshold of 0.6, suggesting strong indicators for the respective constructs (Data quality, Local Knowledge, Stakeholder Engagement, and Risk Management Effectiveness). The variance inflation factor (VIF) results show that all indicators fall within acceptable levels, meaning multicollinearity does not pose a problem in the analysis.

In Table 3, discriminant validity is assessed using the heterotrait–monotrait ratio (HTMT). All HTMT values remain below the recommended cutoff of 0.85, indicating that the constructs are clearly differentiated. Table 4 presents the R^2 and Q^2 values used to judge the explanatory and predictive strength of the model. With an R^2 value of 0.616, the model shows a moderate level of explanatory power. All Q^2 values are greater than zero, indicating that the model has predictive relevance. Among the constructs, RME records the highest Q^2 value (0.485). This suggests that stakeholder engagement and risk management processes contribute meaningfully to the effectiveness of rural energy projects, whereas data quality and local knowledge play a more limited role in this specific context.

In structural equation modelling, a Q^2 value above zero signals that the model has predictive relevance for a reflective endogenous construct. Hair et al. (2014) explain that values around 0.02 indicate low predictive relevance, 0.15 indicate moderate relevance, and values near 0.35 or above indicate high relevance. These values help determine how well the model accounts for variance in the dependent constructs. As shown in Table 4, the Q^2 values for all constructs exceed zero, confirming predictive relevance. RME shows strong predictive power (Q^2 = 0.485), while SE records moderate predictive relevance (Q^2 = 0.360). In contrast, DI and IK show relatively low predictive relevance, consistent with earlier findings that their direct influence on risk management effectiveness is modest. Table 4 further reports f^2 values, which indicate the effect size of each predictor on the endogenous constructs. These values help clarify the contribution of each variable. For instance, the f^2 value for DI on RME shows whether improvements in data quality make a meaningful difference in explaining variations in project outcomes. Stakeholder engagement shows the strongest effect size among the predictors, reinforcing its central role in supporting effective risk management in rural energy initiatives.

Taken together, the Q^2 and f^2 statistics provide a broader picture of the model's performance. The results show that stakeholder engagement and effective project management practices are the most important determinants of risk management effectiveness, while data quality and local knowledge play smaller supporting roles. The findings also correspond with the assumptions of Information Asymmetry Theory and the Dynamic Capabilities View. Information Asymmetry Theory highlights the problems that arise when stakeholders have unequal access to information. Although DI shows a smaller effect compared with SE, its positive influence on RME suggests that addressing information gaps can still improve decision-making in rural energy projects. This is particularly relevant in project environments where reliable information is often scarce. The Dynamic Capabilities View stresses the importance of an organisation's ability to adapt, learn, and reconfigure its resources. The strong effect of stakeholder engagement supports this view, showing that active involvement and collaboration among all parties including local communities, implementers, and government bodies enhance a project's ability to respond to emerging risks. While local knowledge contributes positively, its impact is more effective when combined with adaptive capabilities and continuous learning mechanisms.

Table 5 summarises the structural model results used to test the study's hypotheses. The path coefficient for DI → RME is 0.146, with a T-statistic of 2.442 and a p-value of 0.007, indicating a positive and statistically significant relationship. This supports the argument that better data quality reduces information gaps and strengthens project decision-making. The relationship between IK and RME is also significant. The path coefficient of 0.420 (T-statistic = 4.864, p < 0.001) shows that local knowledge enhances project outcomes, although its influence is not as strong as stakeholder engagement. From a dynamic capabilities perspective, local knowledge helps identify context-specific risks and opportunities, but its full value emerges when organisations are able to integrate and adapt this knowledge. Stakeholder engagement has the strongest effect on rural energy project outcomes, with a coefficient of 0.420, a T-statistic of 2.838, and a p-value of 0.002. This highlights its essential role in promoting shared decision-making and joint responsibility for risk management. The ability to draw on diverse perspectives, coordinate activities, and maintain open communication enhances overall project effectiveness. This aligns with theoretical expectations that dynamic, collaborative structures are vital for managing complex risks in rural energy projects.

Table 5: Hypothesized relationships between Data Quality (DI), Local Knowledge (IK), Stakeholder Engagement (SE), and Rural Energy Outcomes (RME)

Hypothesis	Path coefficient	Standard deviation	T-statistics	P-values
DI -> RME	0.146	0.076	1.915	0.028
IK -> RME	0.420	0.099	4.250	0.000
SE -> RME	0.289	0.089	3.232	0.001

Source: Data analysis from field data (2024): $p < .05$

Discussion of Findings

This study investigated how adverse selection influences risk management in rural energy projects in Tanzania, with particular attention to the roles of data quality, stakeholder engagement, and the use of local knowledge. The findings shed light on how these factors operate jointly to shape project outcomes. The results indicate that data quality exerts a moderate but significant positive influence on project outcomes ($\beta = 0.146$, $p = 0.028$). This supports the central ideas of Information Asymmetry Theory, which argues that when stakeholders hold unequal or incomplete information, poor choices and coordination failures become likely. Improving the availability and reliability of project information helps close these gaps and supports better decisions. However, its effect in this study is smaller than that of stakeholder engagement and local knowledge. This suggests that while high-quality data is useful, it must be combined with strong collaboration among project actors to fully improve outcomes. Stakeholder engagement shows the strongest effect on rural energy project performance ($\beta = 0.289$, $p < 0.001$). This finding is consistent with the Dynamic Capabilities View, which emphasises the value of adaptive and flexible responses to changing environments. When communities, government institutions, and private actors participate actively, projects benefit from shared insights, smoother coordination, and earlier identification of risks. These results align with earlier studies, such as Adebayo et al. (2024), Kumaraswamy (2024), and Hindarto (2023), which all highlight how collaborative practices strengthen the likelihood of success in complex or resource-constrained settings conditions that are typical in rural energy projects in Tanzania.

Local knowledge integration also demonstrates a strong and significant effect on outcomes ($\beta = 0.420$, $p < 0.001$). This supports the value of context-specific knowledge, as emphasised by the Dynamic Capabilities View. Local communities often have insights into cultural patterns, environmental conditions, and social dynamics that external actors may overlook. These insights help refine project design and support early risk identification. However, its influence is most effective when paired with strong stakeholder engagement, suggesting that local knowledge alone cannot resolve the broader structural and institutional challenges faced by rural energy projects. Prior studies such as Aben et al. (2021), Amin et al. (2023), and Leal Filho et al. (2024) show similar patterns. The PLS-SEM results, taken together, demonstrate that the combination of stakeholder engagement, data quality, and local knowledge provides a more complete explanation for risk management effectiveness than any single factor alone. Data quality reduces information gaps, stakeholder engagement promotes shared responsibility, and local knowledge ensures projects are grounded in local realities. This combination is central to navigating risks and supporting project success. From a practical standpoint, the findings provide several lessons. Training programs that improve project managers' skills in participatory decision-making and community coordination would strengthen implementation. Digital information-sharing tools can reduce information gaps and help ensure that stakeholders are kept updated. Equally important is the need to systematically gather and apply local knowledge throughout the project cycle not only during early planning phases. These measures can help rural energy projects adjust more effectively to uncertainties, reduce operational risks, and enhance long-term sustainability.

Conclusion

The evidence points to stakeholder engagement as the most influential factor shaping the success of rural energy projects in Tanzania. This aligns with the Dynamic Capabilities View, which highlights the ability of organisations to respond effectively to changing circumstances by drawing on a variety of knowledge sources and competencies. Active involvement of community members, local leaders, government bodies, and private actors helps projects identify risks earlier, coordinate more effectively, and respond efficiently as challenges arise. Local knowledge furthermore strengthens project relevance and sustainability by ensuring that plans and interventions align with social norms, cultural expectations, and community priorities. However, the study also notes that local institutional factors such as traditional governance structures, local regulation, and community hierarchies can either support or hinder the effective application of local knowledge (Gossal, 2025; Olawoyin, 2025). These factors should therefore be considered in any framework for improving risk management in rural energy initiatives. Although data quality contributes to better decision-making, its effect is smaller compared to the other two variables. Information Asymmetry Theory helps explain this pattern: improving access to reliable information matters, but it does not replace the need for trust-building, transparency, and collaborative action. Data alone cannot overcome structural or cultural challenges unless stakeholders engage actively and communicate openly. The study's cross-sectional nature limits conclusions about how these relationships develop over time. Future research could use longitudinal designs to observe how stakeholder engagement, information access, and local knowledge evolve and interact as projects progress. Additionally, examining broader political and economic conditions may offer a deeper understanding of the factors that shape project success or failure in rural Tanzanian contexts.

Implications

The study strengthens the application of Information Asymmetry Theory and the Dynamic Capabilities View in understanding rural energy project performance. Information Asymmetry Theory highlights that imbalances in information hinder risk management, especially in rural areas where access to accurate data may be limited. Ensuring that stakeholders are properly informed helps reduce misunderstandings and supports more aligned decision-making. The Dynamic Capabilities View supports the finding that effective risk management depends on an organisation's ability to integrate community knowledge, adjust strategies, and remain responsive. This challenges conventional top-down project management approaches by highlighting the need for flexible systems that draw from multiple sources of expertise. In terms of methodology, the study demonstrates the usefulness of quantitative methods in analysing risk management in rural environments. Engaging local actors in data collection ensured that project realities were properly captured. This approach provides a model for similar studies conducted in rural or data-poor areas.

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