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Bankability Assessment of Lithium-ion and Vanadium Redox Flow Batteries in Kenyan Hybrid Renewable Energy Systems

George Omondi Otieno Meyo[1], John Nderu[2], and Lucas Ongondo Mogaka[3]

[1]Department of Electrical and Electronic Engineering, Murang'a University of Technology, Kenya
[2]Department of Electrical and Electronic Engineering, Jomo Kenyatta University of Agriculture &Technology, Kenya
[3]Department of Electrical and Electronic Engineering, Meru University of Science &Technology, Kenya

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Corresponding author:
George Omondi Otieno Meyo,
okebejnr@gmail.com

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Abstract: Reliable and affordable electricity remains essential for rural development; however, in Sub-Saharan Africa (SSA), particularly Kenya, the major barrier to scalable rural electrification is increasingly the bankability gap, where technically feasible Hybrid Renewable Energy Systems (HRES) fail to attract sustainable investment. This study evaluates how battery storage technology selection influences investment viability by comparing lithium-ion (Li-ion) and vanadium redox flow battery (VRFB) systems in a rural Kenyan HRES. An integrated framework combining Homer Pro optimization, project-level financial modelling, Life Cycle Assessment (LCA), and AHP-based Multi-Criteria Decision Analysis (MCDA) was applied to assess techno-economic performance, environmental sustainability, and investor attractiveness. Results show that Li-ion systems achieve stronger short-term financial bankability, with lower Levelized Cost of Storage (LCOS) of KSh 23.17/kWh compared to KSh 28.32/kWh for VRFB systems, alongside higher baseline Investor Attractiveness Index (IAI). However, Li-ion technologies exhibit higher lifecycle environmental burden and replacement risk. In contrast, VRFB systems demonstrate lower emissions, longer operational lifetime, and stronger suitability under concessional and sustainability-oriented financing structures. Sensitivity analysis reveals that battery bankability depends not only on technical performance but also on financing structure, discount rate, and investor class.

Keywords Bankability gap, Hybrid Renewable Energy Systems (HRES), Lithium-ion (Li-ion), Vanadium Redox Flow Battery (VRFB)

1. Introduction

Reliable and affordable electricity underpins global development; however, electricity scarcity remains prevalent in rural regions where energy poverty constrains healthcare, education, enterprise development, and digital inclusion (Devarajan et al., 2026). In Kenya, national electrification strategies have progressed well despite many households in remote Arid and Semi-Arid Lands (ASALs) remaining underserved due to prohibitive grid extension costs, dispersed settlement patterns, and uncertain revenue structures (World Bank, 2024). Recently, decentralized Hybrid Renewable Energy Systems (HRES), integrating solar photovoltaic (PV), wind, and battery energy storage, are gaining traction as a technically feasible alternative for rural electrification (Muchiri et al., 2023; Ahmed & D'Angola, 2025).

However, while prior research has largely focused on technical optimization, cost minimization, and technology suitability, the central challenge facing many rural HRES projects is increasingly financial deployability (Devarajan et al., 2026; Bui & Le, 2026). These projects have sometimes failed to secure sustainable financing since engineering feasibility does not automatically translate into investment attractiveness (Ahmad et al., 2026). This therefore constitutes the financial viability gap, that is, a project's ability to attract debt and equity financing under acceptable risk-adjusted return conditions, driven by predictable cash flows, manageable lifecycle risks, and lender confidence (Gatti, 2023). It is the structural mismatch between technical feasibility and financing feasibility caused by uncertainty in lifecycle cost, replacement risk, environmental liabilities, and policy compatibility (Bui & Le, 2026; Ahmad et al., 2026). In rural HRES, this distinction is critical as technically optimized systems may remain financially non-deployable if storage technologies introduce excessive capital intensity, replacement risk, or ESG liabilities. This study therefore conceptualizes the bankability gap as a project-finance failure condition where engineering viability does not translate into investible infrastructure. To improve practical relevance, the modeling assumptions were additionally benchmarked against reported operational characteristics of Kenyan rural mini-grid systems.

Energy storage systems are central to this challenge since they represent the most capital-intensive and financially sensitive component of HRES infrastructure (Gupta & Suhag, 2022; Ahmed & D'Angola, 2025). Battery selection directly influences upfront capital requirements, replacement cycles, operational reliability, debt-service capability, and lifecycle sustainability. Thus, storage technology choice is no longer merely a technical design decision; it is a core determinant of project bankability (Bhattacharyya, 2024).

Li-ion batteries dominate current rural deployments due to declining capital costs, high efficiency, and technical maturity supporting short term affordability and rapid deployment (Ahmed & D'Angola, 2025; Elliot et al., 2025). However, degradation, thermal sensitivity, and replacement frequency weaken long-term financial resilience (Hemmati et al., 2024). In contrast, VRFBs offer extended lifetimes, minimal degradation, and strong recyclability, but are constrained by high upfront capital costs which often reduce attractiveness under conventional financing models (Hou et al., 2024; Ahmed & D'Angola, 2025).

This creates a strategic financing dilemma: Li-ion systems may outperform under commercial, cost-sensitive capital structures, while VRFBs may offer superior value under concessional, patient-capital, or sustainability-linked financing ecosystems (Bui & Le, 2026; Ahmad et al., 2026).

Kenya's ASAL context provides a relevant environment for evaluating this trade-off due to high ambient temperatures, strong renewable potential, infrastructure deficits, and policy-driven off-grid investment initiatives such as KOSAP (World Bank, 2024; Kenya Meteorological Department [KMD], 2020). Existing studies in rural HRES literature predominantly examine technical, economic, or environmental dimensions in isolation, with limited integration of investor-oriented financial viability frameworks (Digkoglou et al., 2024; Devarajan et al., 2026).

Therefore, this study addresses the gap by reframing battery technology assessment from "Which battery performs best technically?" to "Which battery most effectively bridges the gap between technical feasibility and sustainable investment?"

With limited integration of project finance indicators, such as discounted cash flow resilience, debt-service capability, and investor-class-specific capital compatibility, current studies inadequately explain why technically optimal systems often fail to achieve deployment. This study addresses this gap by reframing battery selection as a financing feasibility problem, evaluating storage technologies as investment assets within a project-finance-oriented framework.

Unlike previous HRES studies that primarily focus on technical optimization, cost minimization, or environmental performance independently, this study integrates project-finance indicators, lifecycle environmental risk assessment, and investment viability metrics within a unified decision framework. The novelty lies in treating battery selection as an infrastructure finance problem rather than a purely engineering optimization problem.

The aim of this study is to:

1. Evaluate and compare the techno-economic, environmental, and financing feasibility performance of Li-ion and VRFB systems.

2. Assess lifecycle financial viability using project-finance-oriented indicators such as LCOS, NPC, NPV, IRR, DPP, DSCR, and the IAI.
3. Analyze financing scenario and identify conditions under which technology preference shifts under varying discount rates and capital structures.
4. Provide policy and investor-oriented recommendations for strategic battery deployment.

2. Materials and Methods

2.1 Case Site Description

Imbirikani, located in Kajiado county, Kenya, was selected as a representative ASAL case site for rural HRES deployment due to its climatic, technical, and financial characteristics relevant to off-grid electrification (World Bank, 2024; [KMD], 2020). The area experiences high solar irradiance of 5.5-6.5kWh/m²/day, moderate wind complementarity, dispersed settlements, weak grid penetration, and significant unmet electricity demand (Muchiri et al., 2023; [KMD], 2020). The community load profile comprised households, small businesses, schools, health facilities, and water pumping services, characterized by evening peak demand and moderate seasonal variability associated with climatic and socio-economic activities.

Average daily electricity demand for the modeled community was estimated as 2,850 kWh/day, with a peak demand of 245 kW occurring between 18:00 and 22:00 hrs., reflecting dominant residential and commercial evening consumption patterns. The community load profile was synthesized from reported electricity consumption characteristics of Kenyan rural mini-grid projects and KOSAP demand assessment studies, incorporating household consumption, productive energy use, social services, and community infrastructure loads representative of ASAL settlement patterns. The resulting load model was subsequently implemented in HOMER Pro to simulate realistic rural electricity demand conditions. Seasonal load variation of ±12% was incorporated to account for climatic effects on water pumping, cooling demand, and productive energy activities. The modelled communities comprised approximately 420 households, 18 small businesses, 2 primary schools, 1 health facility, and communal water pumping services representative of rural ASAL settlement structures in Kajiado County. A projected annual load growth of 2% was adopted to reflect increasing rural electrification uptake and productive energy use under programs such as the Kenya Off-Grid Solar Access Program (KOSAP) (World Bank, 2024). These characteristics make Imbirikani an approximate proxy for evaluating the technical feasibility and financial bankability of rural HRES under uncertain revenue and infrastructure conditions (Devarajan et al., 2026; Bui & Le, 2026).

2.2 HRES Configuration

The modeled HRES comprised a Solar PV array, Wind turbine, Li-ion or VRFB battery storage system, and bidirectional power converter integrated within a fully off-grid architecture. Homer Pro optimization determined the optimal configuration based on minimum Net Present Cost (NPC) while maintaining less than 1% unmet load and a renewable fraction exceeding 80%. The optimized system incorporated appropriately sized PV generation as the primary energy source, moderate wind capacity to enhance resource complementarity, and battery storage sized to ensure supply reliability during low-generation periods. Converter sizing was matched to peak load and battery dispatch requirements to maintain stable system operation. A load-following dispatch strategy was adopted to prioritize renewable energy utilization while minimizing excess generation and storage cycling. The optimized Li-ion configuration consisted of approximately 320 kW PV capacity, 80 kW wind generation, 600 kWh battery storage, and 250 kW bidirectional converter capacity. Under equivalent reliability constraints, the VRFB configuration required slightly higher storage sizing due to lower round-trip efficiency but achieved comparable renewable penetration exceeding 80% under annual operating conditions. Battery degradation behavior was incorporated through temperature-sensitive Li-ion performance and long-cycle VRFB operational characteristics (Hemmati et al., 2024; Hou et al., 2024).

With the HOMER Pro Optimization Parameters illustrated in Table 1, simulations were conducted using an hourly time-step over a 20-year project horizon. Sensitivity analyses were performed across battery cost scenarios and discount-rate assumptions. The optimization process evaluated multiple combinations of PV capacity, wind generation, battery storage size, and converter ratings within predefined search spaces to identify configurations that minimize NPC while satisfying reliability constraints. A load-following dispatch strategy was selected based on its suitability for maximizing renewable utilization and reducing unnecessary battery cycling in rural off-grid applications.

Table 1 Homer Pro Optimization Parameters

Parameter	Range
PV size	200–500 kW (20 kW step)
Wind	0–120 kW (20 kW step)
Li-ion	200–1000 kWh
VRFB	200–1200 kWh
Converter	150–300 kW
Solar data source	NASA POWER
Wind data source	KMD
Dispatch	Load following

2.3 Techno-Economic and Financial Modeling Framework

This framework was structured in line with core project finance principles, energy storage technologies evaluated as infrastructure assets based on capital structure resilience, discounted cash flow performance, lender security, and lifecycle reinvestment risk. Unlike conventional cost-minimization approaches, this framework incorporated both return-based metrics (NPV, IRR) and debt viability metrics (DSCR), aligning battery selection with infrastructure investment decision-making.

A project-level financial model developed integrated standard investment metrics such as NPC, LCOS, NPV, Internal Rate of Return, Discounted Payback Period, and Debt Service Coverage Ratio.

This study adopts a synthetic infrastructure-finance modelling approach due to limited public availability of operational mini-grid financial datasets in Kenya.

2.3.1 Validation of Financial Assumptions Against Kenyan Mini-grid Economics

The techno-economic and financing assumptions adopted in this study were benchmarked against reported cost structures of Kenyan and East African rural mini-grid projects. Storage CAPEX, discount rates, load growth, and operational assumptions were aligned with KOSAP-related deployment data, recent rural electrification studies, and energy-storage literature (World Bank, 2024; Thango & Obokoh, 2024). The baseline discount rate of 10% reflects prevailing commercial infrastructure financing conditions in Sub-Saharan Africa, while the 6% concessional scenario represents climate-finance and donor-supported rural electrification structures. Battery lifetime and replacement assumptions were further validated using manufacturer datasheets and recent battery deployment studies. Although operational financial datasets for Kenyan mini-grids remain limited, the adopted parameter ranges remain consistent with reported rural HRES economics and operational mini-grid characteristics in Kenya as illustrated in Table 2 and the operational benchmark validation presented in section 2.3.2.

The adopted financial assumptions were selected to reflect realistic rural mini-grid financing conditions in Kenya, enabling standardized comparison of lifecycle bankability across storage technologies.

These assumptions were informed by prevailing financing conditions for rural renewable energy projects in Kenya and Sub-Saharan Africa. The 20-year project lifetime was selected to capture long-term infrastructure performance and battery replacement cycles, while discount rates of 6%, 10%, and 14% represented concessional, baseline commercial, and high-risk private financing environments, respectively.

The 70:30 debt-equity structure reflects common mini-grid financing arrangements reported in rural energy finance literature. Battery replacement costs, O&M costs, and electricity tariffs were benchmarked against recent market studies, regulatory references, and manufacturer data to improve the realism of projected cash flows and bankability outcomes.

Table 2 Project Finance and Economic Assumptions Used in the Bankability Model

Parameter	Value	Unit	Rationale/Bankability relevance	Source
Project lifetime	20	Years	Typical rural HRES investment horizon	HOMER Pro default/ literature
Nominal discount rate (baseline)	10	%	Reflects commercial infrastructure finance in SSA	World Bank (2024)
Concessional discount rate	6	%	Climate-finance scenario	Ahmad et al. (2026)
High-risk commercial rate	14	%	Stress-testing private capital exposure	Sensitivity assumption
O&M escalation rate	2	%/year	Inflation-adjusted maintenance growth	assumption
Debt-equity ratio	70:30	%	Typical mini-grid financing structure	Rural energy finance literature
Electricity tariff	45	KSh/kWh	Reflects off-grid mini-grid environment	EPRA mini-grid benchmarks
Annual growth	2	%	Rural demand expansion assumption	KOSAP projections
PV degradation rate	0.5	%/year	Standard PV aging	Manufacturer data
Converter efficiency	95	%	Standard inverter efficiency	Manufacturer data
Currency basis	Kenya Shilling (KSh)	-	Localized investment analysis	Study basis
Analysis software	HOMER Pro + MATLAB + Excel	-	Multi-platform verification	Study methodology

2.3.2 Operational Benchmark Validation Using Kenyan Mini-grid Data

For practical applicability, selected techno-economic assumptions adopted in this study were benchmarked against reported operational characteristics of Kenyan and East African rural mini-grid systems (World Bank, 2024; Thango & Obokoh, 2024; Muchiri et al., 2023), including electricity tariff range, daily demand, renewable penetration, and financing conditions documented under KOSAP-related deployments, and rural electrification studies. The comparison indicates that the modeled Imbirikani HRES configuration remains within realistic operational ranges reported for projects in Kenya. This benchmarking process also served as an indirect validation of HOMER Pro optimization outputs by confirming that key model outputs, including renewable penetration levels, demand characteristics, tariff assumptions, and financing conditions, were consistent with operational ranges reported for Kenyan and East African mini-grid systems. The agreement between modeled and reported values provides confidence that the simulated bankability outcomes are representative of practical rural electrification settings. Table 3 illustrates this benchmarking, thus improves confidence that the modeled bankability outcomes reflect practical rural electrification conditions.

2.3.3 Net Present Cost (NPC)

NPC was used as HOMER Pro's primary optimization objective, consistent with (Bhattacharyya, 2024):

$$\mathrm{NPC} = \frac{C_{ann}}{CRF(i,N)} \tag{1}$$

Where:

- C_{ann}: total annualized system cost

- CRF: capital recovery factor
- i: discount rate
- N: project lifetime

Capital Recovery Factor:

$$\mathrm{CRF(i,N)} = \frac{\mathrm{i(1+i)^N}}{\mathrm{(1+i)^N-1}} \quad (2)$$

Table 3 Validation of Key Mini-grid Operational and Financial Assumptions.

Operational Parameter	Modeled Value	Reported Kenyan/East African range	Validation Interpretation
Electricity tariff	45 KSh/kWh	35-60 KSh/kWh	Within realistic rural mini-grid tariff range
Daily electricity demand	2,850 kWh/day	1,500-4,000 kWh/day	Consistent with community-scale mini-grids
Peak demand	245 kW	150-350 kW	Representative of productive-use rural systems
Renewable penetration	>80%	70-95%	Consistent with high-renewable mini-grid systems
Annual load growth	2%	1-5%	Consistent with rural electrification expansion trends
Commercial discount rate	10%	8-15%	Reflects SSA infrastructure financing conditions

2.3.4 Levelized Cost of Storage (LCOS)

LCOS served as the core storage affordability metric and was selected due to its relevance in comparing lifecycle cost competitiveness across battery chemistries (Bhattacharyya, 2024; Gupta & Suhag, 2022):

$$LCOS = \frac{\sum_{t=0}^{n}\frac{C_t}{(1+r)^t}}{\sum_{t=0}^{n}\frac{E_t}{(1+r)^t}} \quad (3)$$

Where:

- C_t: annualized cost in year t (CAPEX, O&M, replacement.)
- E_t: energy delivered in year t
- r: discount rate
- n: project life

2.3.5 Net Present Value (NPV)

This was used to determine investor profitability:

$$NPV = \sum_{t=0}^{n}\frac{R_t - C_t}{(1+r)^t} \quad (4)$$

Where:

- R_t: revenue in year t
- C_t: cost in year t

2.3.6 Internal Rate of Return (IRR)

IRR was determined as:

$$\sum_{t=0}^{n}\frac{R_t - C_t}{(1+IRR)^t} = 0 \quad (5)$$

IRR is the discount rate at which NPV=0

2.3.7 Discounted Payback Period (DPP)

DPP measured the time required for cumulative discounted cash flows to recover initial investment:

$$\mathrm{DPP} = \min\left\{t: \sum_{k=0}^{t} \frac{\mathrm{CF_k}}{(1+r)^k} \geq \mathrm{I_0}\right\} \tag{6}$$

2.3.8 Debt Service Coverage Ratio (DSCR)

This was used to evaluate lender confidence and debt sustainability, particularly under capital constrained rural financing conditions (Ahmad et al., 2026).

$$\mathrm{DSCR} = \frac{\text{Net Operating Income}}{\text{Debt Service}} \tag{7}$$

2.3.9 Sensitivity Analysis and Financial Stress Testing

To evaluate financial robustness under uncertainty, a multi-scenario sensitivity framework was carried out with key variables including:

- Battery CAPEX: 0.8×, 1.0×, 1.2×
- Discount Rate: 6%, 10%, 14%
- Load Growth: 0%, 2%, 4%
- Backup fuel cost variability: ±25%

This approach enabled identification of financing scenario reversal points, where the preferred technology shifts depending on capital conditions (Devarajan et al., 2026).

2.3.9.1 Monte Carlo Probabilistic Risk Analysis

Monte Carlo Simulation (MCS) was applied to evaluate bankability under financing and operational uncertainty. Key variables included battery CAPEX, discount rate, load growth (0–4%), replacement cost, and fuel cost variability, represented using literature-informed probability distributions. CAPEX and load growth were modeled using triangular distributions, discount rate using a normal distribution (μ = 10%, σ = 2%), and replacement cost using a lognormal distribution.

A total of 10,000 simulation iterations were conducted using MATLAB and cross-validated in Microsoft Excel to ensure computational consistency. Simulation outputs for NPC, LCOS, NPV, DSCR, and IAI were analyzed using uncertainty metrics including standard deviations, confidence intervals, and probabilities of achieving positive NPV and acceptable DSCR thresholds, thereby enabling probabilistic assessment of financing risk and investment robustness.

2.4 Environmental Assessment (LCA as Bankability Risk Layer)

A cradle-to-grave LCA was conducted in accordance with ISO 14040/14044 standards for environmental life cycle assessment (ISO, 2006; Finkbeiner, 2014). The functional unit was defined as 1 kWh of electricity delivered over the battery lifecycle, with system boundaries covering raw material extraction, manufacturing, transportation to Kenya, deployment, operation, and end-of-life recycling or disposal. Key indicators included GWP, mineral depletion, water footprint, and recycling potential with environmental impacts interpreted as financial risk proxies, reflecting increasing importance of ESG-linked financing (Ahmad et al., 2026).

The environmental assessment was conducted using a literature-based comparative LCA framework rather than process-specific industrial inventory modelling. Lifecycle inventory data and emission factors were synthesized from recent peer-reviewed battery LCA studies and manufacturer technical reports (Hemmati et al., 2024; Zanoletti et al., 2024). Environmental impacts were evaluated using a mid-point impact-oriented approach based primarily on GWP. The impact assessment primarily employed the IPCC 100-year Global Warming Potential characterization method (GWP100) to quantify lifecycle greenhouse gas emissions. Additional indicators including recyclability potential, mineral resource depletion, and water footprint were incorporated qualitatively to provide a broader environmental perspective relevant to ESG-linked investment decision-making. Since the analysis was comparative and deterministic, allocation procedures followed proportional attribution of lifecycle impacts reported in the source literature rather than primary process allocation modelling.

The comparative LCA was conducted using literature-derived lifecycle inventory datasets synthesized in Microsoft Excel rather than dedicated process-based LCA such as OpenLCA. Emission factors were harmonized from recent peer-reviewed battery lifecycle studies and manufacturer technical documentation to ensure consistency across battery technologies. GWP values were standardized using IPCC 100-year characterization factor (GWP100) to improve comparability of lifecycle carbon impacts. Because the assessment was comparative and literature-based, allocation procedures followed proportional attribution of impacts as reported in the source studies rather than primary process-level allocation modelling.

2.5 AHP-Based MCDA Analysis

Weights for three criteria were derived by use of AHP as Financial (0.40), Technical (0.30), and Environmental (0.30)

These weights were adopted from literature consensus on infrastructure investment priorities emphasizing financial viability at 40% over technical and environmental considerations at 30% each, consistent with the previous MCDA-based renewable energy investment studies (Boumaiza et al., 2022).

The AHP implementation followed Saaty's pairwise comparison methodology. The decision hierarchy consisted of the overall objective (bankability assessment of battery storage technologies), three evaluation criteria (financial, technical, and environmental dimensions), and two alternatives (Li-ion and VRFB). Pairwise comparison matrices were developed based on literature-informed investment priorities, after which matrix normalization was performed and priority vectors were derived using the principal eigenvector approach. Consistency of pairwise judgments was subsequently assessed through the Consistency Index (CI) and Consistency Ratio (CR), with CR values below 0.10 considered acceptable for decision reliability.
Pairwise comparison consistency was validated using the Consistency Ratio (CR), with an acceptable threshold of CR less than 0.1 (Saaty, 1980).

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{8}$$

where:

$$\mathrm{CI} = \frac{\lambda_{\mathrm{max}} - \mathrm{n}}{\mathrm{n} - 1} \tag{9}$$

λ_{max}=Maximum eigenvalue.
RI= Random Index

2.6 Investor Attractiveness Index (IAI)

The IAI was developed as a composite bankability indicator integrating financial, technical, environmental, and financing-related criteria through an AHP-weighted aggregation approach. The IAI was calculated as:

$$IAI = \sum_{i=1}^{n} w_i N_i \tag{10}$$

Where:
w_i represents AHP-derived weight assigned to criterion i.
N_i represents normalized performance score of criterions i
n is the total number of evaluation criteria.
Performance indicators were normalized using min-max scaling:

$$N_i = \frac{X_i - X_{min}}{X_{max} - X_{min}} \tag{11}$$

for benefit criteria, while cost criteria were normalized using:

$$N_i = \frac{X_{max} - X_i}{X_{max} - X_{min}} \quad (12)$$

The IAI computation involved four sequential steps. First, financial, technical, environmental, and financing-related indicators were identified to reflect multidimensional aspects of battery bankability. Second, the performance indicators were normalized using min-max scaling to ensure comparability across differing measurement units. Third, the normalized scores were weighted using the AHP-derived criterion weights. Finally, the weighted scores were aggregated to generate a composite score for each battery technology. Higher values therefore reflect stronger alignment with investor expectations regarding profitability, operational reliability, environmental sustainability, and financing feasibility.

The IAI incorporated financial indicators including LCOS, NPV, IRR, and DSCR; technical indicators including battery operational lifetime and replacement frequency; and environmental indicators represented by Global Warming Potential (GWP) and recyclability performance. Following normalization using min-max scaling, these indicators were weighted using AHP-derived criteria weights and aggregated to generate composite investment attractiveness scores for each battery technology.

This IAI integrated capital accessibility, lifecycle profitability, replacement risk, ESG compatibility, policy alignment, and financing sensitivity, thereby transforming HRES assessment into a bankability-centered investment decision model (Devarajan et al., 2026; Ahmad et al., 2026). This integrated framework forms the basis for the sequential workflow presented in Figure 1 below.

Table 4 Bankability-Oriented Techno-Economic, Financial Risk, and Investment Parameters

Parameter	Unit	Li-ion (LFP)	VRFB	Bankability Relevance	Data Source
Capital cost (CAPEX)	KSh/kWh	57,924	90,104	Evaluates capital and financing burden, and short-term investor entry barrier	Olabi et al. (2023); Thango and Obokoh (2024); Hemmati et al. (2024)
Replacement cost	KSh/kWh	25,744	45,052	Influences lifecycle risk, and long-term cash flow projection	Olabi et al. (2023); Hemmati et al. (2024)
O&M cost	KSh/kWh/year	1,287	1,931	Affects recurring operational expenditure and annual revenue retention	Hemmati et al. (2024); Olabi et al. (2023)
Round-trip efficiency	%	92	75	Impacts energy revenue conversion efficiency and cost competitiveness	Olabi et al. (2023); Hemmati et al. (2024)
Operational lifetime	Years	10	20	Impacts asset lifetime, debt horizon relevance, and infrastructure durability	Olabi et al. (2023); Hemmati et al. (2024)
Cycle life	Cycles	6,000	13,000	Relates to degradation risk, replacement frequency, and lifecycle financial resilience	Olabi et al. (2023); Hemmati et al. (2024)
Depth of discharge	Percentage	80–90	100	Affects usable capacity, flexibility of a project, and return on installed storage assets	Olabi et al. (2023)
End-of-life recyclability	Percentage	Moderate (<50%)	High (>80%)	Affects residual asset value, environmental compliance, and sustainability-linked financing attractiveness	Zanoletti et al. (2024); Olabi et al. (2023)
Technology maturity	Qualitative	High	Moderate	Determines lender confidence, deployment familiarity, and perceived investment security	Rezaee and Silva (2026)

The values were synthesized from recent literature as indicated and validated against manufacturer technical datasheets.

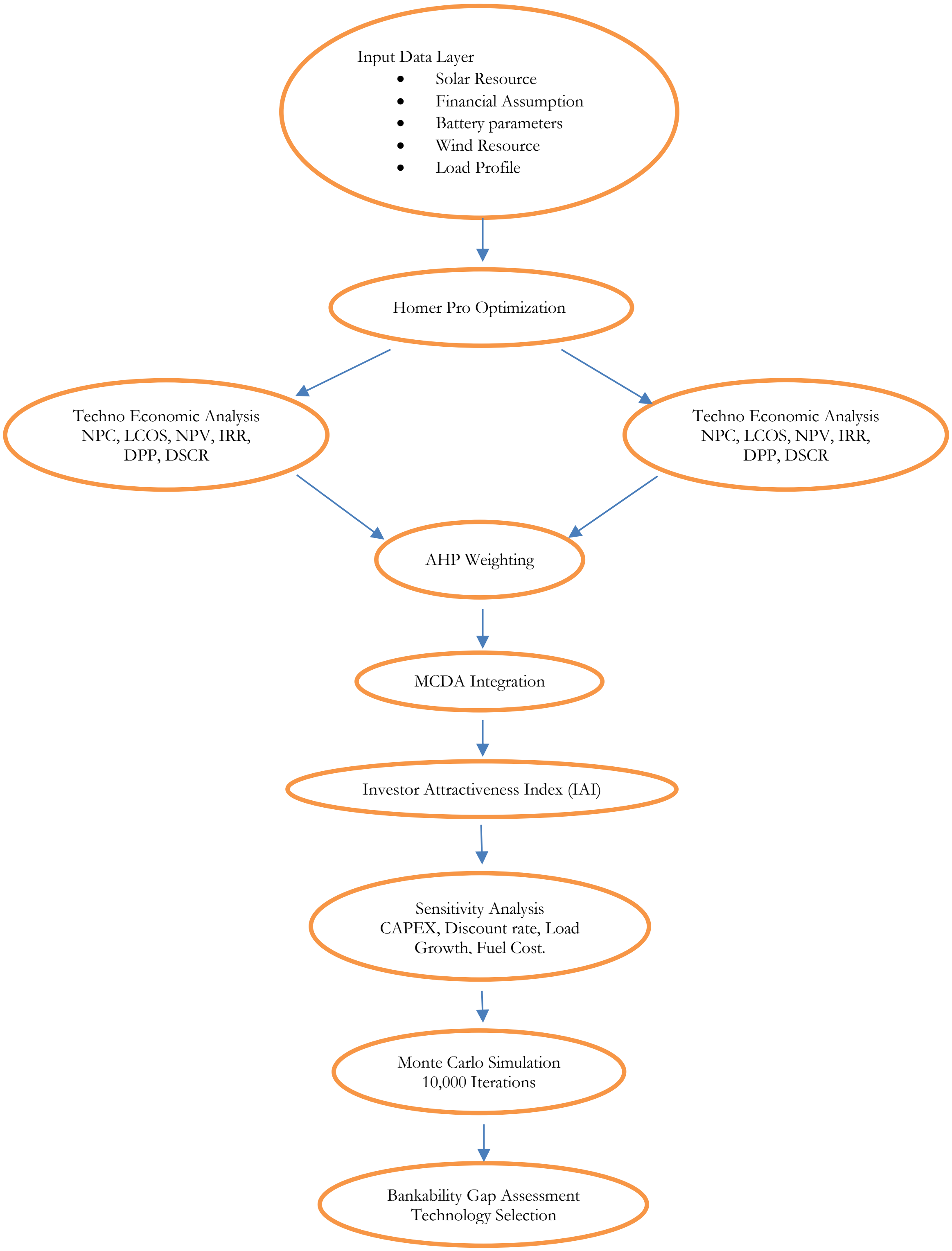

Figure 1 Sequential Integrated Workflow

3. Results and Discussion

3.1 Integrated Bankability Performance of Li-ion and VRFB Systems

The integration of HOMER Pro optimization, lifecycle financial modeling, Life Cycle Assessment, and Investor Attractiveness Index analysis, demonstrated that Li-ion systems dominate under short-term, cost-sensitive financing structures, while VRFB systems gain comparative advantage under long-horizon, concessional, and sustainability-linked financing frameworks.

3.2 Short-Term Financing Feasibility

Under baseline financing conditions of 10% discount rate, Li-ion systems demonstrate better short-term financial performance, achieving a lower LCOS of 23.17 KSh/kWh compared to 28.32 KSh/kWh for VRFB systems. Similarly, the NPC is lower for Li-ion at KSh 669.34M than for VRFB at KSh 823.81M, indicating a reduced initial capital burden as presented in Table 5.
This advantage is primarily driven by:

- Lower capital expenditure (CAPEX)
- Higher round-trip efficiency, between 90 % and 92%.
- Faster revenue recovery profiles

From a financial perspective, these characteristics translate into higher Internal Rate of Return, shorter Discounted Payback Period, and improved lender confidence. Furthermore, the higher technological maturity of Li-ion systems, reflected in their extensive deployment experience and established supply chains, contributes to investor confidence and perceived investment security compared with emerging large-scale VRFB applications (Rezaee & Silva, 2026).

Table 5 presents the integrated techno-economic and project-finance performance of both storage technologies under baseline market financing conditions, combining HOMER Pro optimization outputs with lifecycle investment viability indicators to provide a consolidated assessment of short-term bankability.

Table 5. Baseline Financial and Bankability Performance of Li-ion and VRFB Systems

Financial Metric	Unit	Li-ion	VRFB	Interpretation
Net Present Cost (NPC)	KSh million	669,340,000	823,810,000	Li-ion exhibits lower lifecycle project cost under baseline financing conditions
Net Present Value (NPV)	KSh million	184,600,000	121,800,000	Li-ion provides stronger near-term profitability
LCOS	KSh/kWh	23.17	28.32	Li-ion demonstrates stronger short-term cost competitiveness
Internal Rate of Return (IRR)	%	16.8	11.9	Li-ion exceeds commercial lending expectations
Discounted Payback Period (DPP)	Years	7.2	11.4	VRFB experiences slower capital recovery
Debt Service Coverage Ratio (DSCR)		1.48	1.29	Li-ion demonstrates stronger debt resilience
Replacement Frequency (20-year horizon)	Cycles	1-2	0-1	VRFB reduces reinvestment and refinancing pressure over project lifetime.
Baseline Investor Attractiveness Index (IAI)	-	0.62	0.38	Li-ion is more attractive under conventional market financing conditions.
Profitability Risk		Lower	Moderate	VRFB profitability depends on concessional financing

Despite the stronger short-term financial performance of Li-ion systems presented in Table 5, lifecycle durability considerations increasingly influence long-term financing feasibility outcomes over extended project horizons.

3.2.1 Debt-Service Coverage Ratio (DSCR)

Under baseline financing conditions, Li-ion technologies demonstrate stronger short-term DSCR performance due to lower upfront capital requirements and faster revenue recovery, compared to VRFB technologies which exhibit lower early-stage DSCR values because of higher initial investment costs, although their long-term cash flow stability improved after ten years due to reduced replacement expenditure. Nevertheless, both technologies maintained average DSCR values above the minimum lender acceptability threshold of 1.20. This indicates that both remain financeable under structured rural infrastructure financing frameworks, with Li-ion more attractive under conventional commercial lending and VRFB increasingly competitive under concessional finance conditions, as illustrated in Table 6.

Table 6. DSCR Performance Under Baseline Financing Conditions.

Metric	Li-ion	VRFB	Interpretation
Average DSCR	1.48	1.29	Both exceeded minimum lender threshold.
Minimum DSCR	1.21	1.08	VRFB exhibits tighter debt coverage during early years
Peak DSCR	1.76	1.58	Li-ion demonstrates stronger short-term repayment capability
Years below DSCR 1.2	0	2	VRFB experiences moderate early financing pressure
Lender Risk Profile	Moderate	High	VRFB requires concessional support mechanism

3.2.2 Monte Carlo Probabilistic Investment Viability Analysis

The simulation outputs demonstrated that Li-ion technologies exhibit a higher probability of maintaining positive NPV under baseline commercial financing conditions compared to VRFB systems. Li-ion also exhibited narrower uncertainty ranges and stronger lender acceptability, indicating greater short-term financing certainty. In contrast, VRFB technologies showed wider uncertainty distributions due to higher sensitivity to upfront CAPEX, although downside risk reduced significantly under concessional financing conditions.

Table 7 summarizes the probabilistic uncertainty metrics derived from Monte Carlo analysis, including mean values, standard deviation, and 95% confidence intervals for key financial indicators under baseline financing conditions, indicating stronger short-term financing certainty.

Table 7. Monte Carlo Uncertainty Metrics Under Baseline Financing Conditions

Metric	Li-ion	VRFB	Interpretation
Mean NPV (KSh million)	185	122	Li-ion exhibits stronger expected profitability
NPV standard deviation (KSh million)	38.4	62.7	VRFB demonstrates higher financing uncertainty.
95% CI for NPV (KSh million)	109.3-259.8	-1.2-244.7	VRFB outcomes more sensitive to financing conditions.
Probability of positive NPV	91%	68%	Li-ion shows stronger baseline investment confidence
Probability of DSCR >1.2	88.6%	71.5%	Li-ion exhibits stronger lender acceptability.
Mean LCOS (KSh/kWh)	23.17	28.32	VRFB remains more cost sensitive under baseline financing.

3.2.3 Monte Carlo Risk Interpretation and Financial Robustness Analysis

The Monte Carlo simulation results provide additional insight into the robustness of investment outcomes under financing and operational uncertainty. The probability density distributions indicate that Li-ion systems exhibit a narrower spread of NPV outcomes, reflecting lower investment uncertainty and stronger short-term financing predictability. Conversely, VRFB systems display wider NPV distributions due to greater sensitivity to initial capital expenditure and financing conditions.

The cumulative probability analysis further demonstrates that Li-ion technologies maintain a higher likelihood of achieving positive NPV and satisfying minimum lender acceptability thresholds under baseline financing conditions. Specifically, the probability of achieving positive NPV exceeded 90% for Li-ion systems compared with approximately 68% for VRFB systems, confirming stronger baseline investment confidence.

Tornado sensitivity analysis identifies discount rate and battery CAPEX as the most influential determinants of bankability outcomes. These variables exert the greatest impact on NPV, LCOS, DSCR, and overall Investor Attractiveness Index. Replacement cost and load growth exhibit moderate influence, whereas fuel-cost variability demonstrates comparatively lower sensitivity. This finding suggests that financing structure remains a more critical determinant of project bankability than operational uncertainties. The probabilistic assessment therefore confirms that battery technology preference is highly dependent on financing conditions. While Li-ion technologies offer stronger short-term financial certainty under commercial lending environments, VRFB systems become increasingly competitive when concessional finance, lower discount rates, or sustainability-linked investment mechanisms are available.

3.3 Lifecycle Environmental and ESG-Linked Bankability

Whereas Li-ion technologies exhibit stronger short-term financial investment attractiveness, LCA results show that long-term is significantly influenced by environmental and ESG performance. Li-ion recorded a higher GWP than VRFB, largely due to mineral-intensive manufacturing, critical material dependence, and lower recyclability associated with Li-ion production and recycling supply chains (Hemmati et al., 2024; Zeng, 2025). These factors increase exposure to carbon pricing, supply-chain volatility, and ESG-related financing constraints. In contrast, VRFB demonstrates stronger lifecycle bankability through lower emissions, over 80% electrolyte recyclability, reduced mineral depletion, and better alignment with circular economy principles (Olabi et al., 2023; Zanoletti et al., 2024). These attributes improve compatibility with concessional finance, green bonds, and climate-oriented investment frameworks (Ahmad et al., 2026).

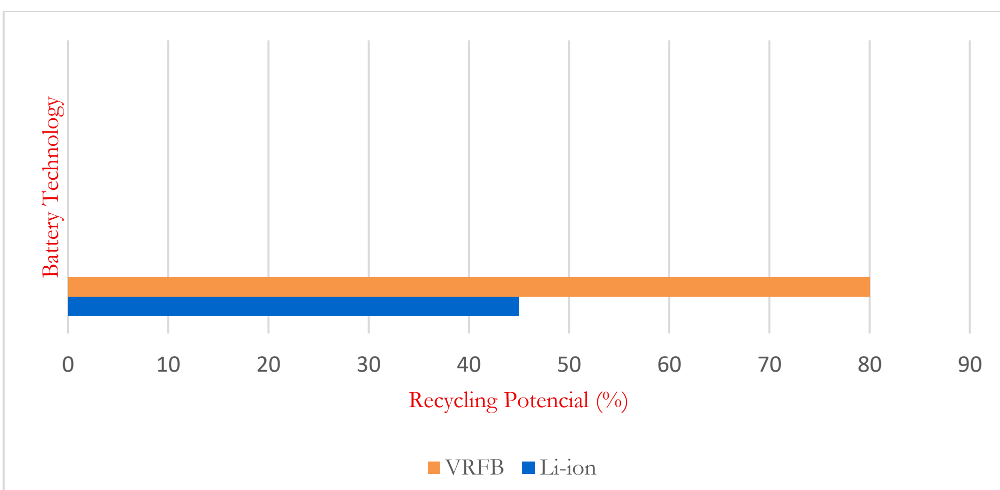

Figure 2a. End-of-Life Recycling Potential of Li-ion and VRFB

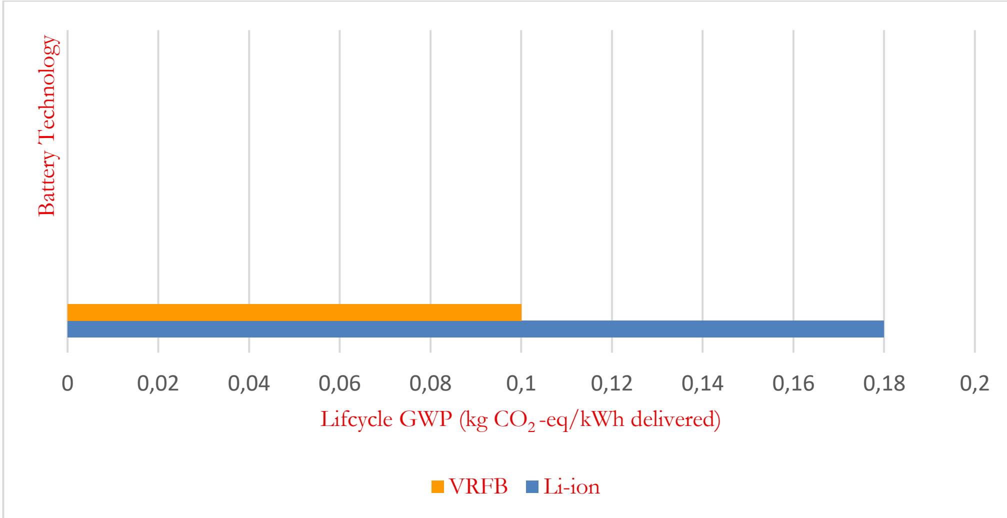

Figure 2b. Lifecycle GWP Comparison of Li-ion versus VRFB

Thus, Li-ion remains more suitable for short-term, cost-driven deployment, whereas VRFB offers stronger long-term environmental and ESG-linked deployability. Figure 2a compares the end-of-life recycling potential of both battery technologies, while Figure 2b indicates approximately 44% lower lifecycle GWP (kg CO_2-eq/kWh delivered) for VRFB relative to Li-ion technologies. Environmental indicators were derived from literature-based lifecycle inventory datasets and therefore represent comparative deterministic estimates. The integrated environmental and ESG financing potential comparison of both technologies is represented in Table 8.

Table 8. Integrated Environmental and ESG financial viability Comparison

Environmental / ESG Metric	**Li-ion (LFP)**	**VRFB**	**Bankability Implication for Rural HRES Investment**
Global Warming Potential (kg CO_2/kWh delivered)	0.18	0.10	VRFB's lower carbon footprint improves compatibility with climate finance, carbon-sensitive lending, and ESG-linked infrastructure investment
Recycling Potential (%)	40–50	>80 (electrolyte reusable)	Higher VRFB recyclability enhances circular-economy financing potential, and end-of-life cost recovery
Critical Material Dependency	High (Li, Co, Ni)	Moderate–Low (vanadium largely recyclable)	Li-ion faces greater supply chain volatility and strategic mineral price risk, increasing long-term financing uncertainty
Mineral Resource Depletion Risk	High	Lower	VRFB offers stronger long-term resource security and lower replacement-material vulnerability
Water Footprint (Lifecycle)	Moderate	Moderate–High	VRFB may face water-intensity concerns, but this is partially offset by longer asset life and recyclability advantages
End-of-Life Disposal Liability	Higher	Lower	VRFB reduces disposal risk, regulatory burden, and potential decommissioning liabilities
Environmental Compliance Risk	Moderate–High	Lower	Lower VRFB environmental burden may improve policy support and sustainability-program eligibility
ESG / Green Finance Compatibility	Moderate	High	Li-ion is poorly aligned with concessional finance, sustainability-linked credit, and green investment mandates as compared to VRFB
Carbon Policy Exposure	Higher	Lower	Li-ion more vulnerable to future carbon pricing compared to VRFB
Long-Term Environmental Bankability Score	Moderate	Strong	Li-ion better for immediate deployment economics; VRFB stronger under lifecycle sustainability and ESG-driven investment frameworks

3.4 Investor Attractiveness and Financing Scenario Reversal

IAI provides a measure of lender confidence by integrating financial, technical, and environmental dimensions. Under baseline conditions at 10% discount rate, Li-ion achieves a higher IAI at 0.62 compared to VRFB at 0.38, which therefore confirms its dominance under conventional market financing.

However, sensitivity analysis under concessional conditions of 6% discount rate and reduced VRFB CAPEX, VRFB surpasses Li-ion (IAI: 0.52 vs. 0.48), indicating a scenario reversal in technology preference.

Conversely, under high-cost commercial capital at 14% discount rate, Li-ion dominance intensifies (IAI: 0.71 vs. 0.29), reinforcing its suitability for capital-constrained environments. Figure 3 illustrates this financing scenario reversal, while Table 9 summarizes IAI outcomes across different capital conditions.

Overall, this demonstrates that there is no universally optimal storage technology and battery preference is elastic to financing conditions. The financing scenario reversal demonstrates that battery superiority is capital-structure dependent rather than purely technology-driven, particularly in rural electrification programs supported by climate-oriented finance.

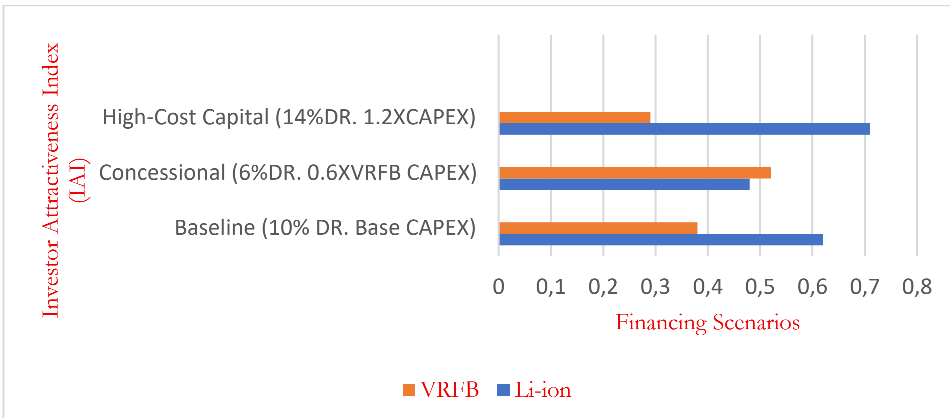

Figure 3. variation of Investor Attractiveness Index (IAI) Under different financing scenarios

Table 9. IAI and Financing Scenario Reversal Analysis

Scenario	Financing Conditions	Li-ion IAI Score	VRFB IAI Score	Dominant Technology
Baseline Market Financing	CAPEX baseline; Discount rate (10%)	0.62	0.38	Li-ion
Concessional Finance / Climate Capital	VRFB CAPEX = 0.8×; Discount rate (6%)	0.48	0.52	VRFB
High-Cost Commercial Capital	CAPEX = 1.2×; Discount rate = 14%	0.71	0.29	Li-ion
ESG-Weighted Long-Term Planning	Extended lifecycle + environmental weighting	0.45	0.55	VRFB
Rapid Least-Cost Deployment	Immediate affordability prioritized	0.68	0.32	Li-ion

3.5 Sensitivity and Robustness Analysis

Sensitivity analysis identified that discount rate and CAPEX as the dominant determinants of financing feasibility outcomes. Lower discount rate significantly improved VRFB competitiveness due to longer operational life and lower replacement requirements.

Similarly, CAPEX reductions through subsidies or concessional financing disproportionately benefited VRFB systems. Load growth and fuel cost variability were found to have minimal effects, probabilistic analysis further identified discount rate and CAPEX as the dominant contributors to IAI uncertainty.

3.6 Comparative Positioning Within Existing Literature

These findings therefore align with previous studies highlighting the cost and efficiency advantages of Li-ion technologies (Gupta & Suhag, 2022; Ahmed & D'Angola, 2025), but extend the literature by demonstrating that battery superiority is financing-context dependent. Unlike conventional studies focused on techno-economic indicators, this study adopts a bankability-centered framework, integrating financial risk, lifecycle sustainability, and investor-oriented metrics. The results further support growing evidence that ESG considerations increasingly influence energy infrastructure financing decisions (Ahmad et al., 2026).

3.7 Closing the Bankability Gap: Integrated Interpretation

The findings indicate that the major constraint to rural HRES deployment is not technical feasibility, but the alignment between technologies and financing structures.

4. Policy Implications and Strategic Deployment Framework

4.1 Reframing Rural Electrification: From Technology Access to Financeable Infrastructure

The findings suggest that rural electrification planning in Kenya and comparable Sub-Saharan African contexts should transition from conventional least-cost deployment approaches toward investment viability -centered infrastructure planning. While technical feasibility and cost minimization remain important, successful deployment of HRES increasingly depends on the alignment between technology performance, financing structures, policy incentives, environmental compliance, and investor risk tolerance.

4.2 Investor-Class-Specific Battery Deployment Strategy

The results indicate battery deployment in rural HRES should be aligned with investor class and financing structure rather than treated as a universal technology choice. Li-ion technologies are more suitable for commercial, cost-sensitive, and rapid-deployment financing environments due to lower upfront CAPEX and stronger short-term financial performance. Conversely, VRFB systems are better aligned with concessional finance, climate capital, and ESG-oriented infrastructure frameworks because of their longer operational life, lower replacement risk, and stronger environmental performance. Accordingly, targeted mechanisms such as subsidies, blended finance, and import-duty incentives may improve VRFB competitiveness and support long-term rural electrification sustainability.

4.3 Strategic Financing Framework for Kenya

This study findings demonstrate that battery deployment should be aligned to financing class as summarized in Table 10 below:

Table 10. Financing–Technology Alignment Matrix

Financing Ecosystem	Preferred Battery	Strategic Logic
Commercial lending	Li-ion	Lower CAPEX, faster returns
Donor least-cost rollout	Li-ion	Immediate affordability
Climate finance	VRFB	ESG + lifecycle resilience
Green bonds	VRFB	Sustainability-linked infrastructure
Public long-term electrification	VRFB	Lower replacement burden
SME mini-grids	Li-ion	Capital accessibility

4.4 Implications for Regulatory Institutions

EPRA: Should incorporate lifecycle financing feasibility, and sensitivity into storage licensing frameworks rather than relying primarily on technical standards.

REREC: Should differentiate battery deployment by geography, that is VRFB under concessional frameworks be recommended for remote, high-risk ASAL zones and Li-ion for rapid deployment be recommended for lower-risk expansion zones.
KOSAP: Should improve deployment sustainability by integrating blended financing structures that strategically support VRFB where long-term resilience outweighs first-cost barriers.

4.5. Limitations and Future Research Directions

This study, conducted in Imbirikani, Kajiado County is limited by its single-case focus, which may constrain broader generalizability across diverse rural contexts. Accordingly, the financing feasibility outcomes represented in this study remain primarily model-based and interpretive, although selected techno-economic assumptions were benchmarked against reported operational characteristics of Kenyan rural mini-grid systems. The analysis also assumes stable policy and regulatory environments, while in practice tariff, subsidy, and carbon pricing changes may significantly affect outcomes. In addition, the AHP-derived weighting introduces inherent subjectivity, which may influence the IAI, and the environmental assessment does not fully capture dynamic ESG financing and evolving sustainability taxonomies.

Future research should expand to multi-site comparative studies, integrate real project finance data from operational mini-grids, and incorporate dynamic policy and market scenarios. Further refinement of the IAI using alternative MCDM techniques and stakeholder-driven weighting is recommended. Extending the framework to include emerging storage technologies and linking investment resilience analysis with blended finance, carbon markets, and green bonds would further strengthen practical and policy relevance.

5. Conclusions

This study developed an integrated bankability-centered framework to evaluate Li-ion and VRFB technologies for rural HRES in Kenya's off-grid ASAL regions. By integrating HOMER Pro optimization, lifecycle financial modeling, LCA, AHP-based MCDA, and IAI, the study extended conventional techno-economic assessment toward financial deployability and investment viability.

The findings indicate that Li-ion batteries provide stronger short-term financing performance under baseline financing conditions due to lower CAPEX, lower LCOS, and higher investor attractiveness, making them more suitable for commercial lending and rapid, cost-sensitive electrification programs. Conversely, VRFB systems demonstrated stronger long-term strategic value through lower lifecycle environmental burden, reduced replacement risk, and improved resilience under concessional and sustainability-oriented financing structures. Sensitivity analysis further showed that lower discount rates and reduced capital barriers can shift investor preference toward VRFB technologies.

Overall, the study concludes that battery superiority in rural HRES is financing-context dependent rather than purely technology-driven. Therefore, optimal battery deployment should align not only with technical performance, but also with financing architecture, investor priorities, and policy objectives.

Declaration of Ethical Standards

As the authors of this study, we declare that we comply with all ethical standards.

Credit Authorship Contribution Statement

Meyo Otieno Omondi George: Conceptualization, Methodology, Software, Validation, Formal analysis, Writing -Original Draft, Visualization.
John Nderu: Methodology, Review & Editing, Supervision, Validation.
Mogaka Ongondo Lucas: Methodology, Writing, Review & Editing, Supervision, Validation.

Declaration of Competing Interest

The authors declared that they have no conflict of interest.

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Data Availability
The data that support this study findings are available upon reasonable request addressed to the corresponding author.

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