Decentralized Solar Powered Water Purification Systems for Off-Grid Communities

Meenakshi R. Tiwari, Purushottam D. Shobhane, Archana Rautela, Limesh Jiyalal Patle, G. Sasikala, D. H. Tupe

Abstract: *This study presents a practice-oriented conceptual framework to support decentralized, solar-powered water purification decisions for off-grid communities where governance and resource constraints often limit service reliability. Existing technology-centric selection approaches rarely map local context to auditable decisions with measurable service proxies, which makes comparisons across programs inconsistent. The proposed model couples water demand and on-site solar energy supply through a nexus-oriented accounting structure, then operationalizes decision rules against three outcomes: water safety compliance rate proxy, energy balance margin percent, and maintenance feasibility score, with explicit boundary conditions and affordability caps. Evaluability is built in through a programmatic cohort validation plan that uses grouped holdouts by geography and context, baseline comparators (simple scoring, regularized feasibility rules, capital-cost-only selection, and single-technology defaults), and leakage controls via entity-identifier splits. Uncertainty reporting is specified using BCa bootstrap 95% CI with alpha 0.05 and 2000 resamples, complemented by rubric coding checks using two annotators with adjudication on a 15% coded sample and deployment-oriented reporting of runtime minutes per 10k records using median and p95 over 5 runs. The resulting artifact is a compact set of constructs, propositions, and decision thresholds (>=95%, >=20%, and >=0.80, each with a 95% CI) intended to guide service providers and community committees in off-grid WASH programs toward safer and more feasible intervention choices.*

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Introduction

Safe drinking water remains difficult to secure in many off-grid settings where scarcity and pollution coexist, and where treatment choices must balance energy, maintenance, and governance constraints. Global syntheses of water purification science underscore that technology options are diverse, yet implementation barriers often determine service continuity (Qi & He, 2025). This study targets the practical decision problem faced by providers and community committees: selecting decentralized, solar-powered purification configurations that can be evaluated against observable service outcomes over time.

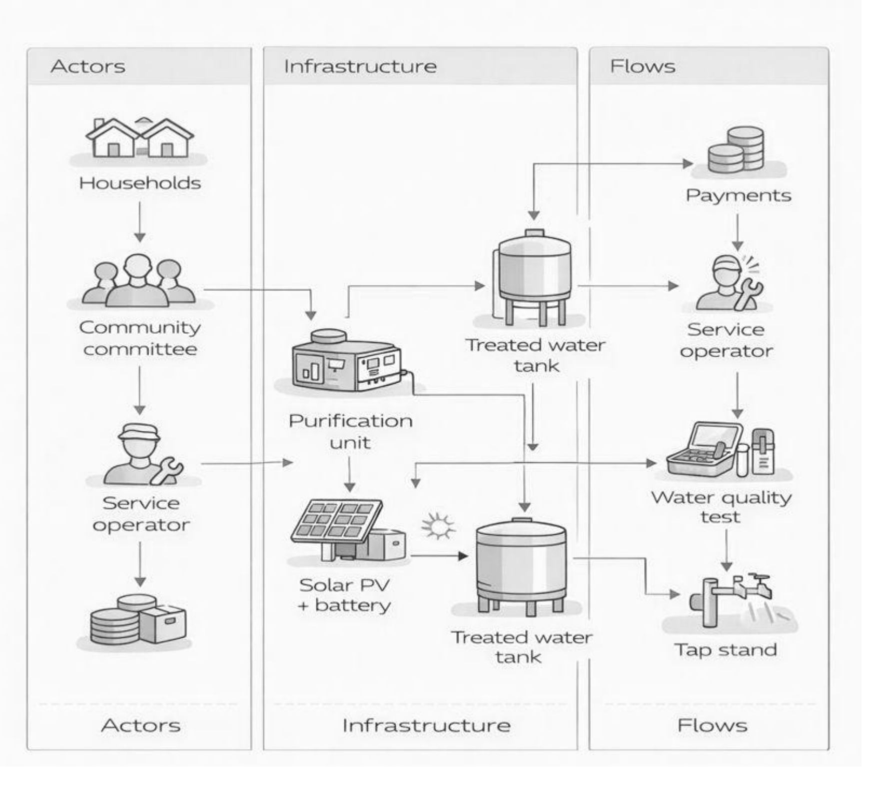

Figure 1. *Off grid purification domain scene*

Solar photovoltaics (PV) can support water services where grid power is unreliable, aligning energy access with broader Sustainable Development Goal (SDG) agendas mapped in bibliometric syntheses (Obaideen et al., 2023). Fig. (1) anchors the argument in an off-grid solar PV water, sanitation, and hygiene (WASH) service scene and clarifies the unit of analysis as a service configuration within a local context. Research design transparency is maintained by stating a conceptual modeling approach with programmatic cohort validation; detailed synthesis steps are not reported here.

Background and Related Foundations

Decentralized water services are commonly framed through nexus perspectives that link water supply, energy inputs, infrastructure reliability, and community engagement, which clarifies why technology choices cannot be evaluated in isolation (Huang et al., 2023). For baselines, these established framings motivate comparing simple scoring, regression-style decision rules, and single-technology defaults as reference points for off-grid purification decisions.

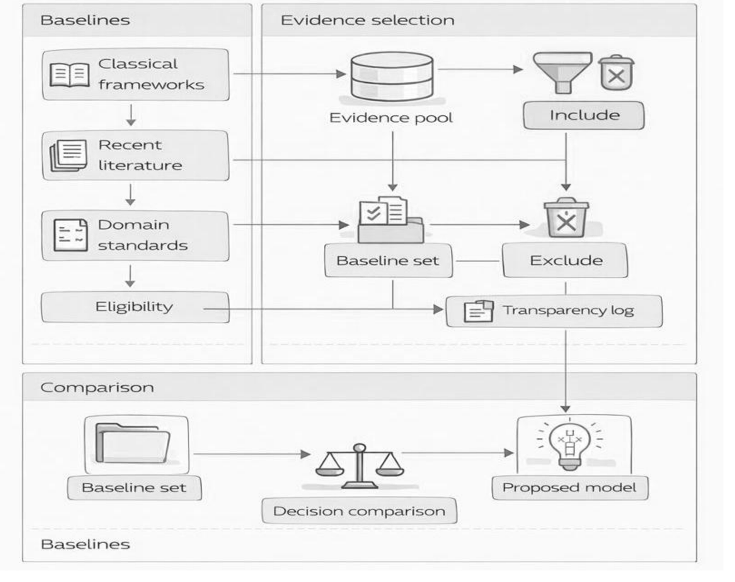

Figure 2. *Baselines and evidence selection flow*

Digitalization of water operations can strengthen monitoring and maintenance planning, yet it introduces practical constraints such as integration cost, system complexity, and data security that shape deployable decision support (Kurniawan et al., 2024). Scenario planning under climate variability adds another baseline: allocation and planning models augmented with machine learning must still manage uncertainty from climate and socio-economic dynamics (Hirko et al., 2025). Fig. (2) contrasts baseline approaches and records evidence inclusion rules; evidence corpus integrity beyond this summary is not reported here.

Conceptual Framework

The conceptual framework links water demand, on-site solar energy supply, and associated emissions through a nexus-oriented accounting structure. Building on joint water-energy-CO2 indicator logic used in district-scale assessments (Romano et al., 2023), this study represents purification as coupled balances. These balances map local context to three decision-facing outcomes: water safety compliance rate proxy, energy balance margin percent, and maintenance feasibility score. The accounting links make trade-offs explicit by expressing each intervention choice as changes in required energy, delivered safe water, and residual emissions.

Interaction framing from basin-scale nexus modeling motivates the emphasis on feedbacks and constraints rather than isolated indicators (Lodge et al., 2024). For deployment in off-grid communities, the model assumes that water quality requirements set a minimum treatment burden. That burden shapes energy needs and, when backup fuels are used, emissions. Competing explanations such as purely cost-driven selection are treated as baselines, and the framework yields observable checks via grouped scenario sweep and assumption sensitivity comparisons.

Key Constructs and Definitions for Solar PV Off-Grid Purification

Consistent coding of off-grid solar PV purification scenarios requires explicit constructs, units of analysis, and measurable proxies. Table (1) defines Water Safety Compliance as a compliance rate proxy, Energy Balance Margin as margin percent, Maintenance Feasibility as a rubric-based feasibility score, and Grouped Holdout Generalization as leave-group-out stability. Conceptual precision is reinforced by mapping monitoring variables such as turbidity and total dissolved solids (TDS) to coded scenario outcomes, following prior sensor-based purifier designs (Bijamwar, 2025). Fig. (3) aligns terminology and units for implementation.

Energy Balance Margin quantifies whether photovoltaic supply can meet the modeled purification load under a given scenario. Equation (1) defines this margin as 100 times the difference between available PV energy and required load energy, divided by the load energy. The same construct supports evaluability of sensor-driven PV pumping control, where real-time signals guide distribution decisions and shape the implied energy balance (Rumbayan et al., 2025). Grouped Holdout Generalization is operationalized through external group splits, indicating stability when geography or context changes.

$$E_{margin}\backslash\% = 100 \cdot \frac{E_{pv} - E_{load}}{E_{load}} \tag{1}$$

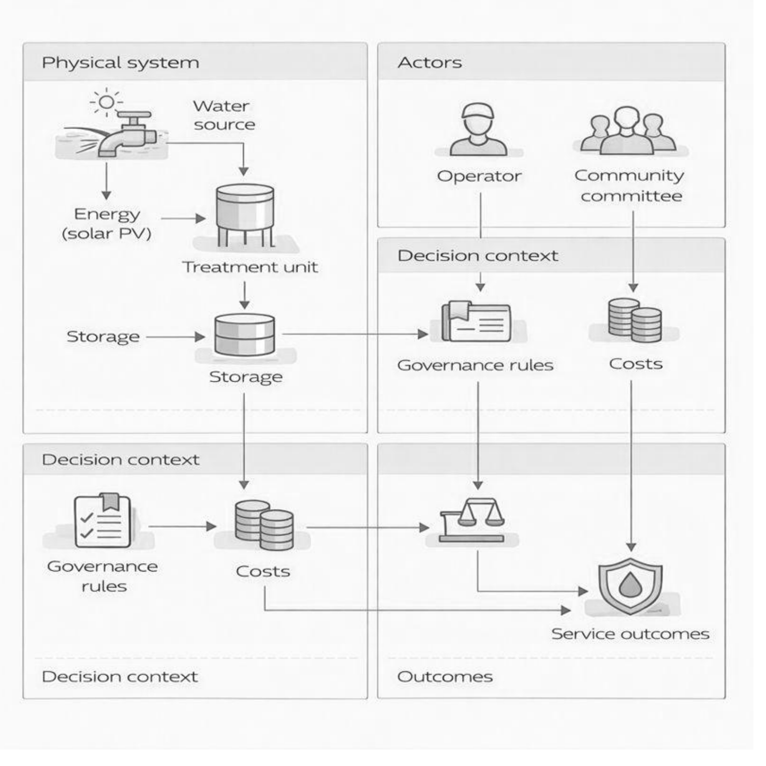

Figure 3. *Core constructs and definitions*

Table 1. Constructs and operational definitions

Construct	*Operational Proxy*	*Measurement Basis*
Water Safety Compliance	Compliance rate proxy	Coded scenario outcome
Energy Balance Margin	Margin percent	Scenario energy balance
Maintenance Feasibility	Feasibility score	Rubric-coded capacity
Grouped Holdout Generalization	Leave-group-out stability	External group splits

Boundary Conditions for WASH Service Level and Affordability Caps

Boundary conditions were specified to keep service-level claims valid in settings characterized by scarcity and intermittent supply, where operational feasibility can dominate nominal design intent (Ayyash et al., 2024). Table (2) lists the minimum bounds, units, and justification sources used to define these boundary conditions. The constraints require water safety compliance >=95%, energy balance margin >=20%, and maintenance feasibility >=0.80. Boundary conditions also include Leave-Group-Out holdouts and a data governance rule of no individual data.

Affordability is treated as a hard cap rather than a preference, so candidate interventions are excluded when projected total costs exceed the allowable ceiling. Equation (2) encodes the affordability boundary condition by requiring total cost to remain below a predefined cap. Climate sensitivity can tighten these feasibility bounds, and reliability-style indicators (reliability, resilience, vulnerability) offer a transparent basis for stress-testing whether minimum service targets remain attainable under adverse weather regimes (Sadowski et al., 2023).

$$C_{tot} \leq C_{cap} \tag{2}$$

Table 2. Boundary conditions and caps

Boundary	*Bound Or Cap*	*Unit Or Scale*	*Justification Source*
Water safety compliance	Greater or equal 95	Percent	Acceptance criteria

Energy balance margin	Greater or equal 20	Percent	Acceptance criteria
Maintenance feasibility	Greater or equal 0.80	Score	Acceptance criteria
Holdout evaluation	Leave-Group-Out	Protocol	Grouped holdouts
Data governance	No individual data	Policy	Policy limits

Causal Mechanisms Linking Governance to Maintenance Feasibility Score

Figure 4. *Mechanism from governance to outcomes*

The proposed causal logic and mechanisms link governance arrangements to the maintenance feasibility score by shaping what actions are feasible under affordability, capacity, and accountability constraints. Fig. (4) formalizes these pathways and states the main assumptions, including that governance features can be proxied with observable program records. The framing targets programmatic cohort comparisons rather than site-specific engineering decisions. Prior evidence that literature-derived parameters support accurate classification from lowresolution water meters motivates this emphasis on operational measurability (Mazzoni et al., 2024).

Table (3) maps each mechanism to an operational cue and measurable implication, enabling empirical checks of the causal chain. Explicit bounds encoding motivates stress-test deltas under resource constraints, and governance feature inclusion can be probed through grouped holdout ablations. Leakage controls rely on entity ID splits and a halt if split audits fail, while uncertainty reporting calls for BCa bootstrap CI to support decision rules. Coding rubric reliability is checked via two-annotator IRR and adjudication (Mazzoni et al., 2024).

Table 3. Mechanisms and testable implications

Mechanism	*Operational Cue*	*Measurable Implication*	*Test Design Cue*
Explicit bounds encoding	Affordability and capacity	Stress test deltas	Resource constraints
Governance feature inclusion	Remove governance features	Ablation performance drop	Grouped holdouts
No leakage controls	Entity ID splits	Stable holdout metrics	Split audit halt
Uncertainty reporting	BCa bootstrap CI	Decision rule check	Seeds and resamples
Coding rubric reliability	Two annotators	IRR and adjudication	15% coded sample

Propositions and Implications

Propositions link off-grid context conditions to technology and service decisions for decentralized, solar-powered purification within WASH programs. The framework treats the decision unit as a community system instance and specifies three observable outcomes: water safety compliance rate proxy, energy balance margin percent, and maintenance feasibility score. Decision rules are framed to satisfy acceptance criteria (>=95, >=20, and >=0.80, each with a 95% CI), enabling comparison against capital-cost-only selection, single-technology default, and two model-based baselines. These propositions target programmatic choice rather than detailed engineering design.

In practical settings, the propositions are intended to be evaluated through programmatic cohort validation with grouped holdouts by geography and context, and explicit controls against cross-split leakage via entity identifiers. Uncertainty quantification follows BCa bootstrap with 2000 resamples stratified by external group, with alpha 0.05 and FDR correction when multiple tests are conducted. Deployment-oriented reporting includes runtime minutes per 10k records and median and p95 runtime over 5 runs. Transfer limits and misuse risks remain material.

Decision Rules for Treatment Trains and Delivery Models

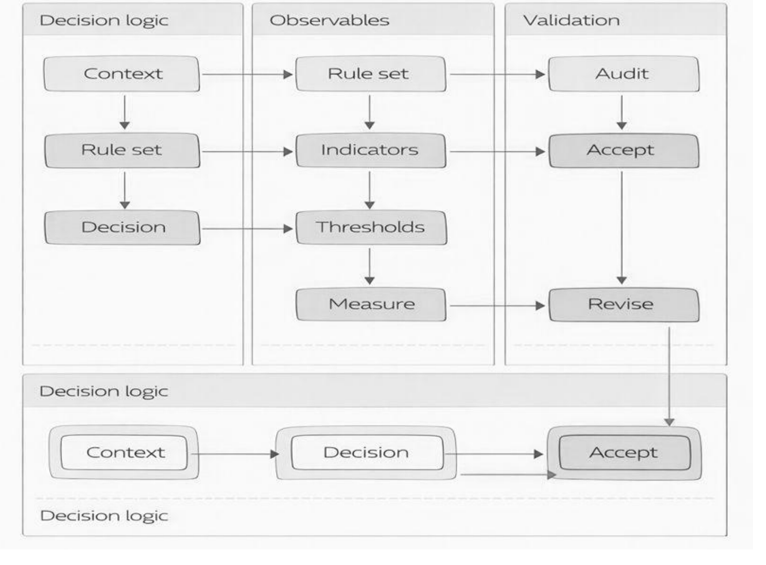

Figure 5. *Decision rules with measurable indicators*

Decision rules translate context variables into treatment-train and delivery-model recommendations that can be audited against measurable service outcomes. Equation (3) defines feasibility by thresholding a computed score into a binary decision. To support evaluability, the score is tied to water safety compliance rate proxy, energy balance margin percent, and maintenance feasibility score, with acceptance criteria (>=95, >=20, and >=0.80, respectively). Site suitability screening can follow GIS-based multi-criteria ranking to pre-filter candidate locations (Lahssaine et al., 2024), while feasibility assumptions can be grounded in PV-powered water-supply evaluations (Mishra et al., 2024).

Fig. (5) links each decision rule to observable field indicators and explicit thresholds, enabling cohort-based validation under grouped holdouts. Delivery models include an optional branch for energy recovery in pressurized distribution networks, where microturbines can replace pressure breaking valves to convert head loss into electricity (Süme et al., 2024). Such options apply only when adequate hydraulic head and institutional capacity exist; otherwise, PV-driven pumping and conventional siting screens remain the relevant decision path (Lahssaine et al., 2024; Mishra et al., 2024).

$$\hat{y} = 1\{s(x) \geq \tau\} \quad (3)$$

Alternative Explanations: Capital Cost-Only and Technology Default Baselines

Alternative explanations are assessed by contrasting the proposed operational decision logic with simplified baselines that omit key constraints in off-grid solar water purification. Table (4) specifies the baselines and competing explanations, ranging from Linear Scoring Baseline and Regularized Feasibility Model to capital-cost-only, single-technology default, and a WEIHN Narrative Alternative. For baselines, weighted-sum scoring and sparse feasibility classification provide transparent comparators. For alternative explanations, technology-only selection is contrasted with scheduling and operational constraints (Loo et al., 2024).

Discrimination relies on observable cues rather than narrative preference. Holdout uplift tests interaction effects beyond linear scoring, governance ablations probe whether feasibility reflects institutional constraints, and safety proxy deltas indicate when capital cost minimization compromises compliance. The single-technology default is challenged via leave-group-out evaluation to expose context heterogeneity. Energy-system-only optimization baselines remain informative for sizing supply, but they ignore service delivery and maintenance feasibility, a limitation common in system-design studies (Mustafa et al., 2022).

Table 4. Baselines and alternatives

Baseline Or Alternative	*Core Decision Logic*	*What It Ignores*	*Discriminator Cue*
Linear Scoring Baseline	Weighted sum score	Interactions, nonlinearity	Holdout uplift
Regularized Feasibility Model	Sparse feasibility classifier	Causal mechanisms	Ablate governance
Capital Cost Only	Min CAPEX choice	Safety, O&M fit	Safety proxy delta
Single Technology Default	One size fits all	Context heterogeneity	Leave group out
WEIHN Narrative Alternative	Nexus framing only (Huang et al., 2023)	Operational constraints	Metric linked targets

Robustness Stress Tests: Solar Seasonality and O&M Capacity Sensitivity

Seasonality is treated as a primary stressor for off-grid solar water purification because seasonal irradiance shifts can tighten the energy balance margin percent and, indirectly, the water safety compliance rate proxy. Scenario-based climate impact analyses illustrate that coupled resource and policy constraints can produce large performance swings, motivating explicit seasonal counterfactuals in the cohort (García et al., 2024). Robustness of reasoning is strengthened when the decision logic is evaluated under both favorable and adverse seasonal resource profiles. The specific seasonality patterns and magnitudes are not reported here.

Operations and maintenance (O&M) capacity is stress-tested via sensitivity sweeps over service staffing and response capability, because maintenance feasibility can limit deployment. Hybrid optimization work in the water-energy nexus indicates that preferred configurations can change when resource availability or backup options differ, supporting capacity perturbations rather than single-point assumptions (Coelho et al., 2024). Robustness of reasoning is improved by verifying whether recommendations stay stable across plausible O&M limits and by identifying regimes where baselines are sufficient. Sweep bounds and outcomes are not reported here.

Validation Plan Using Grouped Holdouts and BCa Bootstrap CI

Grouped holdouts are adopted to evaluate decision rules under geographic and contextual separation, limiting optimistic bias from shared entities. Research design transparency is strengthened by documenting the split strategy and the governance of identifiers used for grouping. Fig. (6) documents the evaluation protocol and how uncertainty will be reported for programmatic cohorts. Table (5) summarizes the planned splits, primary metrics, and uncertainty settings used in the validation protocol (Alzraiee et al., 2024).

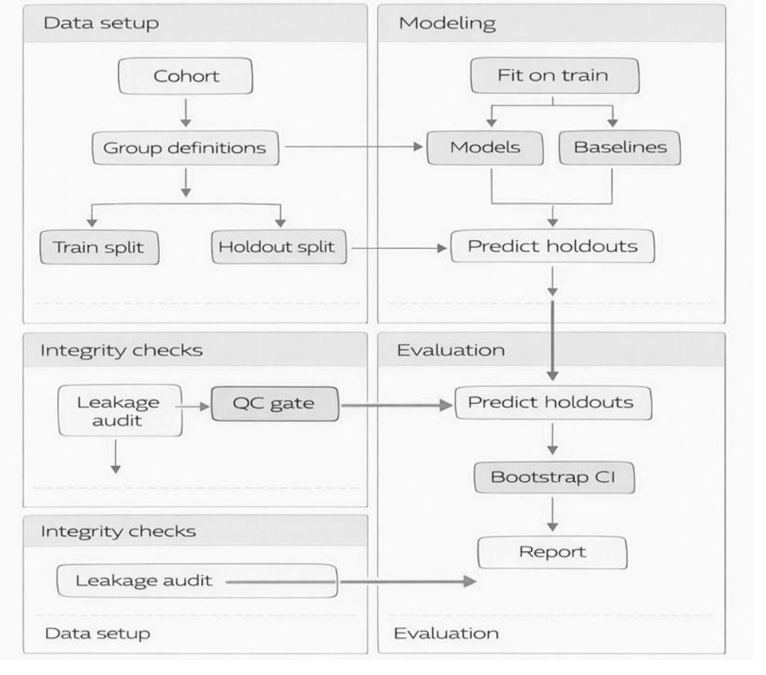

Figure 6. *Grouped holdouts and bootstrap plan*

Evaluability is enforced through observable acceptance criteria and uncertainty bounds rather than point estimates alone. BCa bootstrap uncertainty is specified as 95% CI with alpha 0.05 and 2000 resamples, enabling comparable reporting across holdouts and stress-test conditions. Equation (4) specifies how BCa intervals are constructed for each metric estimate. Robustness checks include stress tests and ablations that remove governance and cost inputs, aligned with bootstrap-based driver analyses used in water and treatment efficiency studies (Maziotis & Molinos-Senante, 2024).

$$CI_{BCa}(\theta) = \left[\widehat{\theta^{*}_{\left(\Phi\left(z_0+(z_0+z_{\alpha/2})/\left(1-a(z_0+z_{\alpha/2})\right)\right)\right)}}, \widehat{\theta^{*}_{\left(\Phi\left(z_0+(z_0+z_{1-\alpha/2})/\left(1-a(z_0+z_{1-\alpha/2})\right)\right)\right)}}\right] \quad (4)$$

Table 5. Validation protocol summary

Element	*Specification*	*Acceptance*	*Notes*
Primary Metrics	Safety, energy, O&M	Meet AC1-AC3	CI reported
Split Strategy	Grouped holdouts	No leakage audit	Entity IDs locked
Uncertainty	BCa bootstrap	95% CI, alpha 0.05	2000 resamples
Robustness Checks	Stress tests, ablations	Holds in holdouts	Remove governance, cost

Limitations and Future Work

Deployment decisions derived from a programmatic cohort remain sensitive to scale assumptions. A central limitation is that learning-curve behavior observed in solar desalination is uneven across technologies, so cost declines cannot be presumed for a specific supply chain or operating context (Wang & He, 2024). Transfer to new geographies may also shift energy balance and maintenance feasibility despite grouped holdouts. Evidence for long-run economies-of-scale in the proposed framework is therefore indicative rather than predictive.

Future work should pair the decision rubric with longitudinal service logs that capture component failures, operator turnover, and supply disruptions, because these factors drive maintenance feasibility in off-grid settings but are not fully represented in the current cohort specification. Related evidence from remote critical-instrument power systems indicates that weather resilience and ongoing upkeep remain practical constraints even when solar is considered low-maintenance (Shadvar & Rahman, 2024). Empirical field evaluations and context-specific coding guidance are not reported here and remain priorities.

Failure Modes: Misuse Guardrails and Water Safety Compliance Proxy Risks

Misuse guardrails are necessary, yet limitations persist, when a water-safety compliance proxy is interpreted as a clinical safety claim. Table (6) catalogs five failure modes that can induce unsafe recommendations and lists corresponding mitigations. Overfit models can create false confidence, a risk amplified in small-sample studies (Alawee et al., 2024). Split leakage inflates metrics, and incomplete reporting of datasets or splits can conceal this failure mode (Sarow et al., 2024; Sharshir et al., 2024). Mis-coding constructs can bias labels; inter-rater reliability (IRR) plus adjudication provides a check.

Boundary conditions become salient when planning constraints are ignored, yielding infeasible deployment choices and service failures. Affordability stress tests and leakage-audit halts operationalize these limits for real-world use, but they cannot substitute for field validation of water-safety outcomes. Modeling and simulation studies can optimize system settings without demonstrating performance under program governance and local behavior (Alsehli, 2024). Overgeneralization remains plausible across geographies, so external group holdouts should be treated as a minimum check rather than proof of transfer (Sarow et al., 2024; Sharshir et al., 2024).

Table 6. Failure modes and guardrails

Failure Mode	***Misuse Risk***	***Impact Cue***	***Guardrail***
Model overfit	False confidence	Unsafe recommendations	Grouped holdouts
Split leakage	Inflated metrics	Wrong selections	Leakage audit halt
Mis-coding constructs	Biased labels	Unfair decisions	IRR plus adjudication
Ignored constraints	Infeasible plans	Service failures	Affordability stress tests
Overgeneralization	Transfer error	Geography mismatch	External group holdout

Conclusion

Nexus-aware modeling can reduce inconsistent technology choices in off-grid solar water purification by making energy constraints explicit alongside water-safety requirements. Evidence from household demand modeling indicates that adding energy features can materially improve explanatory performance, supporting the premise that energy variables are decision-relevant (Li et al., 2024). The present framework operationalizes this logic through explicit propositions, measurable service proxies, and cohort-based validation rules intended to align provider and committee decisions under governance and resource constraints. Integrated optimization of energy generation and water treatment remains a complementary direction for real-world use, particularly when multiple objectives must be balanced across costs, emissions, and reliability. Prior work on coupled power-desalination designs illustrates how multi-objective formulations can expose trade-offs among pollution indices, unit costs, and efficiency (Gharamaleki et al., 2024). Applying similar optimization layers to decentralized solar purification could guide scenario sweeps and stress tests, while remaining within the stated scope that excludes site-specific engineering and clinical trials.

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