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Social Norms and Peer Influence in Rural Hygiene Behaviour Transformation

Jyoti M. Shinde, Roshani Majumdar, Rekha Pal, Priti Golar, Jay Vasani, Valisher Sapayev

Abstract: *This study presents an operational conceptual model of social norms and peer influence in rural hygiene adoption, aimed at improving intervention choices under WASH governance and resource constraints. Existing accounts often describe norms or diffusion qualitatively, leaving limited guidance on how contextual cues translate into decisions that can be evaluated against measurable service outcomes. The proposed framework links subjective norms, peer networks, attitudes, perceived control, and context constraints to a construct-to-decision mapping and coding rubric, with validation planned on the Rural Hygiene Norms and Diffusion Cohort using grouped holdouts and explicit baselines (logistic regression on survey features, graph and information-only comparators, and generic norms messaging). Evaluability is anchored in inter-rater agreement kappa, taxonomy coverage percent, and mechanism-outcome association via Area Under the Curve (AUC), with acceptance criteria set to greater than 0.75, greater than 85, and greater than 0.70, respectively; two annotators labelled a 15% sample with adjudication. Uncertainty reporting follows a BCa bootstrap with 2000 resamples to produce a 95% confidence interval (CI), and robustness is stress-tested with a degradation flag when primary metric CI overlap <=50%. The resulting package clarifies boundary conditions and failure modes while remaining usable as a decision aid, supporting community facilitators and health workers in selecting norms- and network-informed hygiene interventions under affordability and operator-capacity limits.*

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Introduction

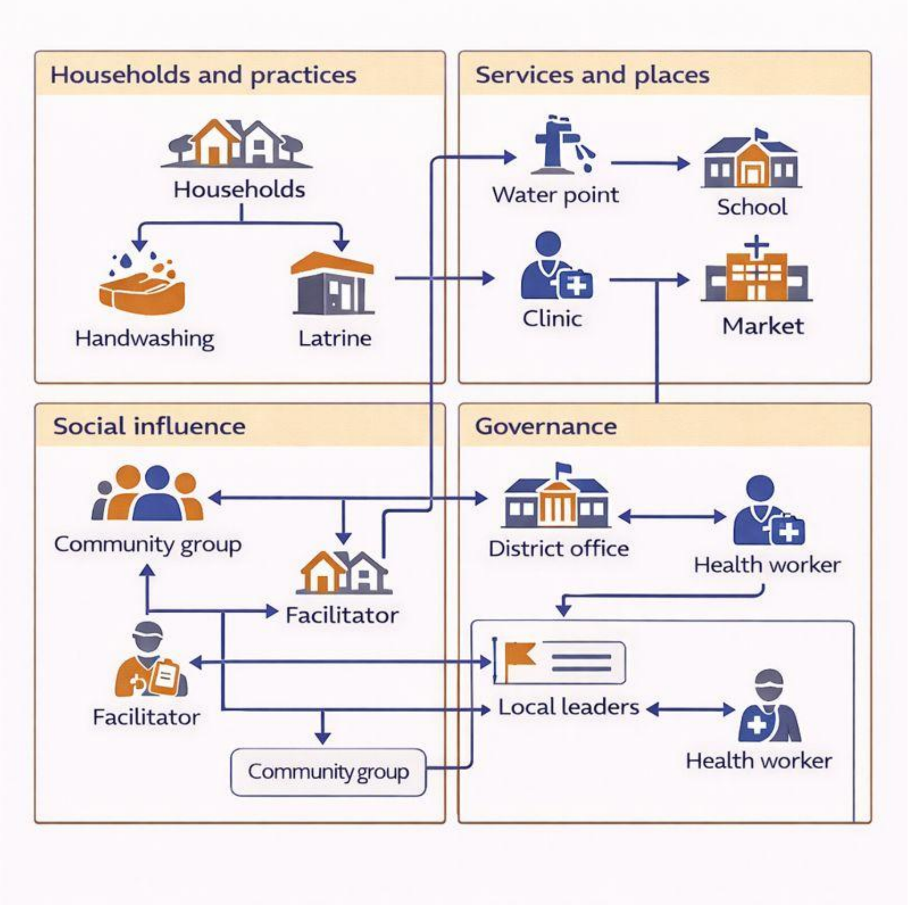

Figure 1. *Rural WASH decision context scene*

Rural hygiene adoption is shaped by social norms and peer influence that interact with material constraints and collective aspirations. A healthy societies framing situates WASH decisions within determinants spanning people, places, products, and planet, rather than treating hygiene as an isolated behaviour (Buse et al., 2023). Fig. (1) anchors the analysis in a rural WASH decision context where practices are interpreted through local networks. Broad Brush Surveys motivate rapid attention to community narratives and social organization (Nel et al., 2023).

Governance and investment constraints can limit the feasibility of upstream action, creating a bias toward individually targeted programs even when community-level drivers are salient (Franz et al., 2023). Research design transparency is maintained by specifying a conceptual synthesis and adaptation workflow: constructs from healthy societies are linked to rapid context assessment indicators, then translated into evaluable propositions and a coding rubric (Buse et al., 2023; Nel et al., 2023). A cohort validation plan is stated to connect the proposed mechanisms to measurable service outcomes, while clinical impact trials remain out of scope.

Background and Related Foundations

Area-level deprivation and vulnerability indices provide pragmatic context, but they are imperfect proxies for individual health-related social needs (HRSNs) (Telzak et al., 2024). As baselines, the Child Opportunity Index (COI) and the Social Vulnerability Index (SVI) represent composite, place-based exposures used widely in observational inference and program targeting (Carroll et al., 2023; Ganguly et al., 2024). Recent SVI reconstructions from 16 American Community Survey (ACS) variables and percentile ranking across counties and ZIP geographies clarify what such measures encode and what they omit (Ng et al., 2025).

Operational use of social determinants of health (SDoH) data is constrained by missingness and inconsistent documentation: structured electronic health record fields are often sparsely completed, and ICD-10-CM SDoH codes are recorded infrequently, with subgroup variation that may reflect practice rather than prevalence (Craven et al., 2024; Llamocca et al., 2024). Evidence corpus integrity therefore depends on transparent inclusion rules and attention to disagreement across settings; those procedures are not reported here. Qualitative WASH insecurity work further underscores heterogeneity that area aggregates can obscure (Anthonj et al., 2024).

Literature Review

Measurement studies on social determinants of health (SDoH) provide baselines for constructing and scoring hygiene-norms instruments. Cognitive interviewing has refined screening items and response options (Adekoya et al., 2023), and SDH-

Q development highlights the importance of psychometric validation before transfer across populations (Sabo et al., 2024). Large-scale survey programs document internal consistency, item non-response, and practical scoring choices (Koleck et al., 2024; Tesfaye et al., 2024). Deployment analyses show that area indices only partially proxy individual needs (Brignone et al., 2024). Complementary risk scoring and text extraction methods foreground trade-offs between coverage and accuracy (Hatef et al., 2024; Kalsi et al., 2024; Ralevski et al., 2024; Sun et al., 2024).

Intervention baselines span multilevel design guidance, randomized evaluations, and rural adoption studies, each offering distinct levers for isolating peer effects (Guilamo-Ramos et al., 2024; Halsall et al., 2022; Phillips & Sullivan, 2023). Rural hygiene evidence links behaviour change to family negotiation and community practice shifts, but also to constraints in product access and uptake (Kawarazuka et al., 2023; Nair et al., 2022; Oli & Woli, 2025). Structural gradients may confound norms-based claims, as illustrated by rural-urban inequality analyses and ecological clustering (Hossain et al., 2023; Jaferian & Farhadian, 2024). Evidence corpus integrity is only partially supported because inclusion and exclusion procedures are not reported here; participatory modeling provides one practical mitigation (Wentworth et al., 2023).

Conceptual Framework

The proposed framework situates rural hygiene adoption as a sequence from social cues to intentions and actionable choices, drawing on mediation patterns reported in prior structural equation modeling evidence (Amat & Wang, 2025). Figure (2) defines the core constructs and their relationships among subjective norms, peer networks, attitudes, perceived control, and context constraints. Conceptual precision is maintained by treating each construct as a distinct mechanism carrier rather than a proxy for behaviour itself.

Table (1) maps each construct to a mechanism cue, a decision lever, and a metric cue, enabling an evaluable link between program design and measurement. Boundary conditions are made explicit by including context constraints with stress-test bounds and holdout stability, clarifying where norm messaging or network targeting may fail under affordability or capacity limits. The mapping follows the indirect-effect logic reported in prior structural equation modeling analyses (Amat & Wang, 2025), but it remains a decision aid rather than a claim of universal causality.

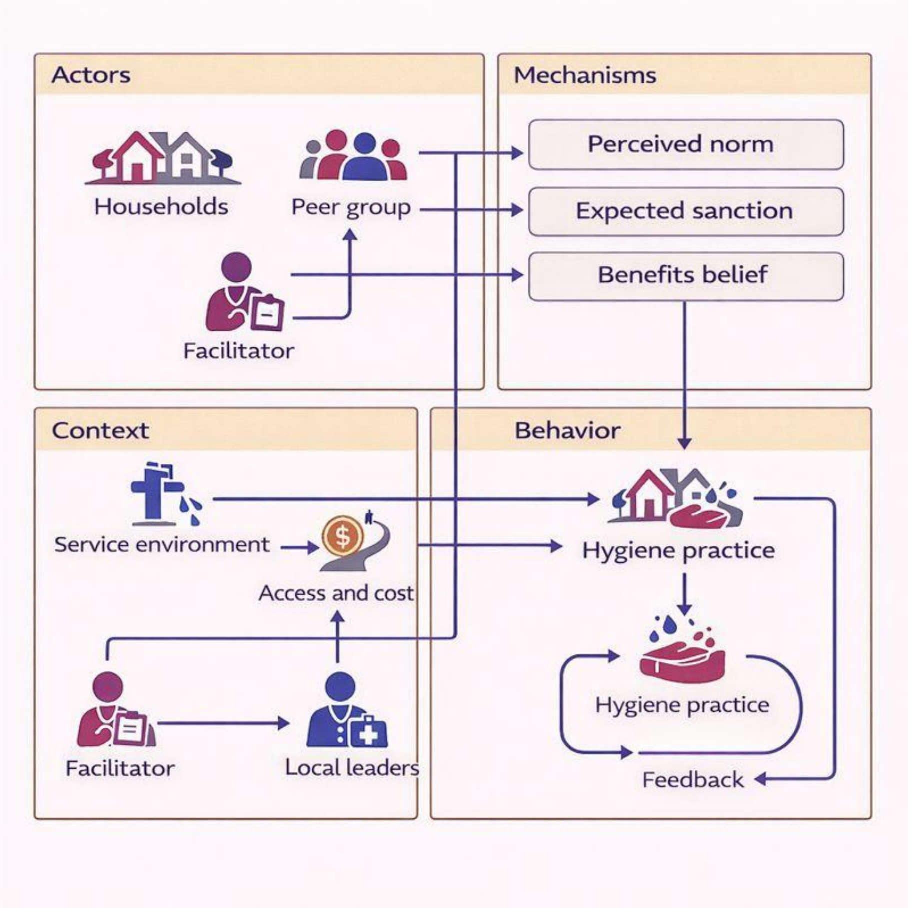

Figure 2. *Constructs and relationships overview*

Table 1. Constructs to decisions mapping

Construct	***Mechanism Cue***	***Decision Lever***	***Metric Cue***
Subjective Norms	Perceived approval	Norm messaging	Taxonomy coverage
Peer Networks	Diffusion pathways	Network targeting (Airoldi & Christakis, 2024)	Mechanism AUC

Attitudes	Valence shift	Benefits framing (Amat & Wang, 2025)	Mechanism AUC
Perceived Control	Self-efficacy barrier	Access enablement	Inter-rater kappa
Context Constraints	Affordability capacity	Stress test bounds	Holdout stability

Key Constructs and Definitions for Social Norms Mechanisms

Key constructs for norms mechanisms are specified as a coding taxonomy that separates perceived prevalence, perceived approval, and influence through social ties. Conceptual precision is maintained by pairing each construct with an observable cue that can be applied consistently during annotation. Table (5) defines Descriptive Norms, Injunctive Norms, Peer Influence, Network Diffusion, and Coding Reliability with prompts such as 'Most neighbours do X', 'Others expect X', and the measurable cue 'Two-degree exposure'.

Reliability and completeness are treated as measurable properties of the coding process, not informal assurances. Equation (1) defines inter-rater agreement kappa for Coding Reliability, enabling a decision rule for whether coder judgments cohere. Equation (2) defines taxonomy coverage percent as the share of items assigned any code, clarifying when the construct set is too sparse for inference. These definitions also constrain interpretation: high prevalence cues need not imply social approval.

$$\kappa = \frac{p_o - p_e}{1 - p_e} \tag{1}$$

$$Coverage = 100 \cdot \frac{N_{coded}}{N_{total}} \tag{2}$$

Table 2. Definitions and operational cues

Construct	***Definition***	***Operational Coding Cue***
Descriptive Norms	Perceived common practice	Most neighbours do X
Injunctive Norms	Perceived social approval	Others expect X
Peer Influence	Adoption shaped by peers	Two-degree exposure
Network Diffusion	Spread via social ties	Nomination central nodes
Coding Reliability	Agreement across coders	Kappa threshold met

Boundary Conditions Across Rural Hygiene Adoption Context Strata

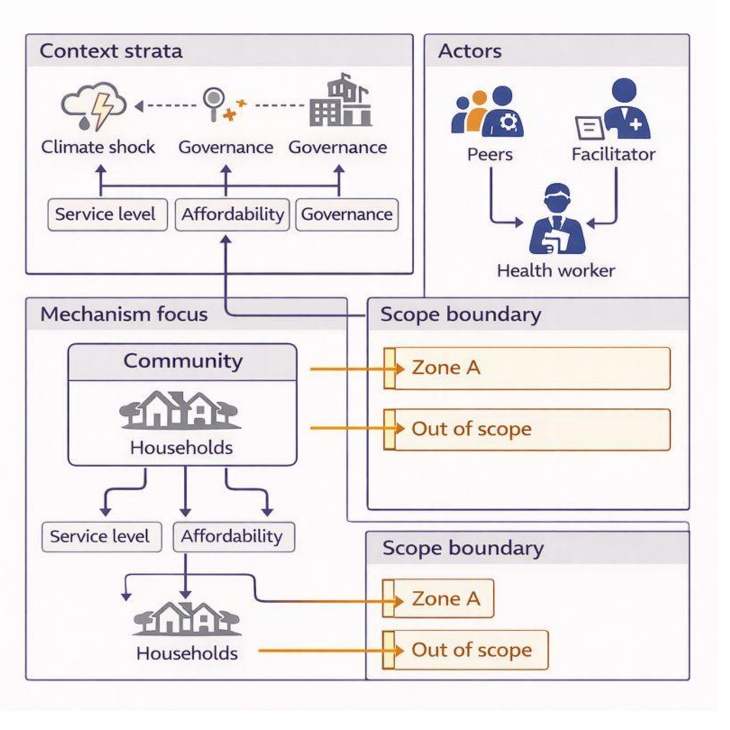

Figure 3. *Applicability zones and boundaries*

Boundary conditions for the proposed framework are anchored in rural hygiene adoption settings where social norms and peer influence plausibly structure household decisions, and where intervention choices must be made under WASH program constraints. Fig. (3) delineates the intended applicability zones and the contexts treated as out of scope. The claims are confined to conceptual mechanisms, propositions, and programmatic cohort validation using public aggregate sources, not to site-specific engineering designs, procurement planning, or clinical health impact trials.

These boundary conditions imply non-applicability when hygiene behaviour is dominated by factors that the model does not represent, including purely hardware-constrained access or administrative mandates that bypass peer-mediated choice. External validity is expected to vary across geographies because the Programmatic Cohort may omit local idiosyncrasies and relies on coded constructs that can be misclassified; measurement-bias sensitivity is therefore central to interpretation. The framework also does not claim that generic messaging is sufficient, absent corroborating cohort outcomes.

Propositions and Implications

Propositions translate the norms-and-peer-influence framework into testable expectations about coding reliability, construct coverage, and mechanism consistency. Table (3) links H1 and H2 to observable metrics, acceptance thresholds, and Grouped holdouts evaluation designs. For causal logic and mechanisms, H1 operationalizes the claim that identified pathways align with outcomes by requiring a Mechanism-Outcome AUC greater than 0.70. For evaluability, acceptance also requires Inter-Rater Kappa greater than 0.75 and Taxonomy Coverage Percent greater than 85 under Grouped holdouts.

Robustness of reasoning is partially addressed through H2, which treats Stress test strata as adversarial slices and requires the Primary metric CI overlap $\le$50% to flag material degradation. This rule guards against conclusions driven by a narrow subset of geographies or normative contexts, but it does not, by itself, isolate causation. Alternative explanations, including performance gains attributable to logistic regression on survey features or single mechanism explanations, are not adjudicated here because comparative results are not reported.

Table 3. Hypotheses and acceptance criteria

Hypothesis	*Metric*	*Acceptance Threshold*	*Evaluation Design*
H1: Beats baselines	Inter-Rater Kappa	Greater Than 0.75	Grouped holdouts
H1: Beats baselines	Taxonomy Coverage Percent	Greater Than 85	Grouped holdouts
H1: Beats baselines	Mechanism-Outcome AUC	Greater Than 0.70	Grouped holdouts
H2: Holds stress tests	Primary metric CI	CI overlap <=50%	Stress test strata

Causal Pathways Linking Peer Influence to WASH Decisions

Peer influence in rural WASH decisions can be framed as diffusion through observed ties rather than isolated persuasion. The causal logic and mechanisms are anchored in evidence that network-based targeting produces village-wide spillovers extending to two degrees of separation, with knowledge spreading more readily than behaviour (Airoldi & Christakis, 2024). In this pathway, treated households transmit information, shift perceived descriptive norms, and provide demonstrations that lower uncertainty about hygiene practices. Effects attenuate with network distance.

Two-degree spillover intuition motivates peer pathway propositions for intervention design. First, information-based components should generate broader indirect reach than practice change, consistent with differential diffusion of knowledge versus behaviour (Airoldi & Christakis, 2024). Costs shape contagion. Second, easier-to-adopt actions should exhibit larger spillovers than capital-intensive upgrades, because social reinforcement cannot fully offset material constraints. Third, nomination-based seeding is expected to outperform random seeding when ties are stable; fragmentation weakens this channel (Airoldi & Christakis, 2024).

Alternative Mechanisms Versus Network Diffusion Model Explanations

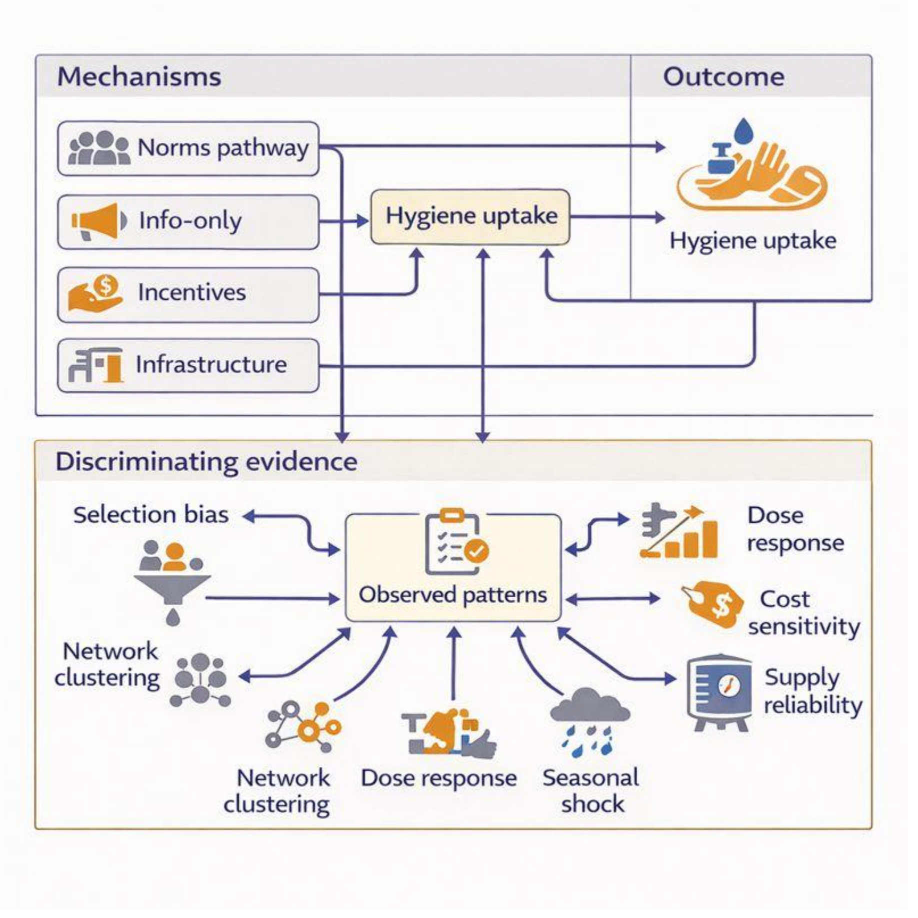

Figure 4. *Competing mechanisms and differentiators*

Attribution of rural hygiene adoption to network diffusion is plausible, yet several alternative explanations can generate similar clustering patterns. These alternative explanations include homophily in peer ties, shared exposure to programs or markets, household constraints that limit action despite intent, and institutional enforcement that induces synchronized change. Alternative explanations therefore serve as a stress test: a diffusion account is preferred empirically only when adoption covaries with network proximity after accounting for shared context and selection.

Fig. (4) contrasts candidate mechanisms and specifies observations that would separate diffusion from confounding processes. Discriminating evidence would emphasize temporal ordering (exposure precedes uptake), tie-specific influence rather than neighbourhood co-trends, and sensitivity to network rewiring or boundary breaks. Evidence of parallel adoption among disconnected households would instead support common shocks or coordinated implementation. Empirical tests and case-selection rules for these contrasts are not reported here, and remain priorities for the cohort validation plan.

Robustness Stress Tests Under Affordability and Climate Constraints

Robust deployment of norms-based hygiene interventions requires checking whether the conceptual links remain stable when affordability and operational constraints tighten. Table (4) enumerates stress tests that translate key levers (cost-feature clipping, response-time limits, leave-group-out splits, entity ID barriers, and assumption sensitivity) into anticipated failure signatures, such as coverage drop or AUC decline. This robustness of reasoning treatment makes the argument falsifiable by pairing each stressor with an observable cue.

Interpretation should distinguish genuine mechanism fragility from artifacts of measurement or sampling. A holdout gap under operator-capacity limits may reflect delayed service delivery rather than weakened peer influence, whereas a train-test delta after a leakage audit more directly signals spurious lift. Kappa decrease under measurement-bias sensitivity indicates that coding constructs are not invariant to assumptions, a boundary condition that constrains transfer across geographies and climatic shocks. Effect sizes for these cues are not reported here.

Table 4. Stress tests and constraints

Stress Test	***Constraint Lever***	***Expected Failure***	***Detection Cue***
Affordability cap	Cost features clipped	Coverage drop	AUC decline
Operator capacity	Response time limit	Service lag	Holdout gap
Grouped holdout	Leave-group-out	Generalization failure	Slice AUC drop
Leakage audit	Entity ID barrier	Spurious lift	Train-test delta
Measurement bias	Assumption sensitivity	Mechanism drift	Kappa decrease

Evaluability: Grouped Holdouts, Baselines, and Bootstrap CI

$$AUC = \int_0^1 rTPR(u)\ du \tag{3}$$

$$CI_{1-\alpha} = \left[\widehat{\theta^*_{(\alpha/2)}}, \widehat{\theta^*_{(1-\alpha/2)}}\right] \tag{4}$$

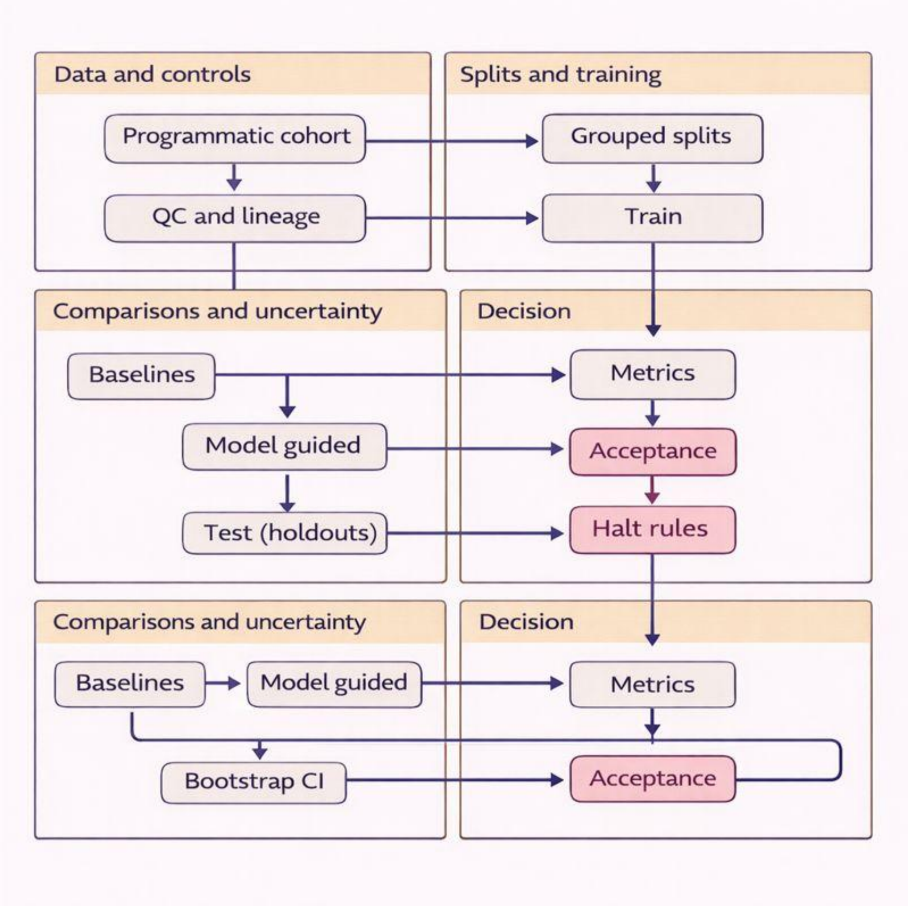

Figure 5. *Evaluation blueprint and acceptance criteria*

An auditable validation plan is required for conceptual claims about norms and peer influence to remain testable under grouped generalization. Table (2) summarizes the split design, baseline set, primary metrics, uncertainty test, and leakage controls that operationalize this requirement. Fig. (5) further traces how grouped holdouts and acceptance cues connect model comparison to decision rules, improving research design transparency. The evaluability signal is anchored in measurable kappa, coverage, and AUC targets rather than narrative plausibility alone.

Baselines are defined as logistic, graph, and info-only comparators, enabling a concrete test of whether the proposed framework adds explanatory value beyond simpler representations. Equation (3) defines Area Under the Curve (AUC) as the integral of the ROC curve, supporting mechanism-outcome association assessment. Uncertainty quantification follows a BCa bootstrap with 2000 resamples, reporting a 95% confidence interval (CI) with FDR control. Equation (4) defines the bootstrap quantile CI used for these intervals.

Table 5. Validation protocol summary

Protocol Element	*Specification*	*Acceptance Cue*
Split Design	Grouped holdouts	Leave group out
Baselines Set	Logistic, graph, info-only	Compare to Proposed
Primary Metrics	Kappa, coverage, AUC	AC1-AC3 thresholds
Uncertainty Test	BCa bootstrap, 2000	95% CI; FDR
Leakage Control	Fit train only	Leakage audit pass

Materials and Methods

The methodological design combined conceptual synthesis with an operational validation plan to translate rural hygiene norms and peer influence mechanisms into decision support for WASH interventions. Research design transparency was maintained by specifying sequential steps: delimiting in-scope claims, formalizing constructs and units of analysis, and deriving evaluable propositions that connect context, normative expectations, and peer exposure to adoption decisions. A coding rubric was then defined to support consistent reviewer annotation and taxonomy coverage assessment.

Planned empirical appraisal used the Rural Hygiene Norms and Diffusion Cohort, a tabular classification dataset grounded in public WASH statistics, with grouped splits defined a priori by geography and contextual entity. Preprocessing was fit on training data only, and a leakage audit halted analysis if entity identifiers crossed splits. Uncertainty was quantified with BCa bootstrap confidence intervals stratified by external group, with false discovery rate correction where multiple hypotheses were tested. Two annotators labeled a 15% sample with adjudication.

Limitations and Future Work

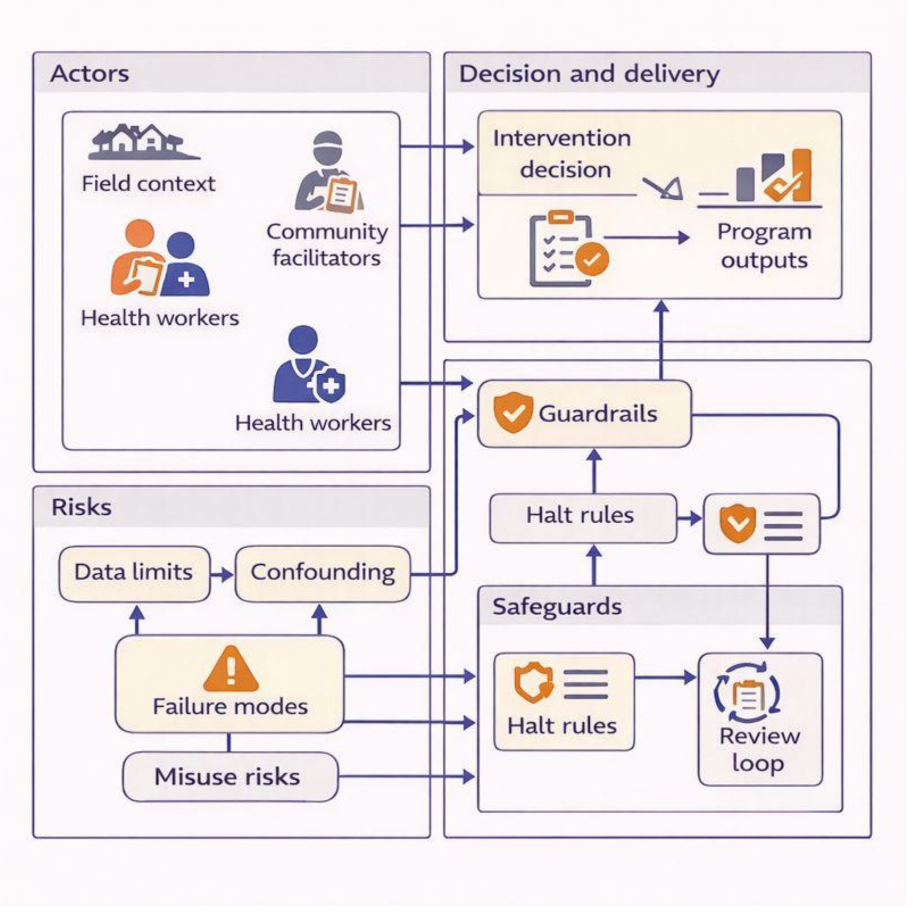

Figure 6. *Failure modes and guardrails*

Several limitations constrain the interpretation and transfer of the proposed conceptual model of norms and peer influence. Table (6) lists key threats, their likely impacts, and corresponding mitigations, including sensitivity ranges to bound local idiosyncrasies and leave-group-out checks for geography transfer risk. Construct miscoding remains plausible despite IRR plus adjudication with Two annotators. Policy misuse risk also persists, motivating explicit boundary cues and parameter bounds rather than universal recommendations.

Future work should test whether the proposed mechanisms retain predictive value when social structure and institutional constraints differ materially, using grouped holdouts and measurement-bias sensitivity analyses already anticipated by the evaluation plan. Fig. (6) summarizes salient failure modes and the associated misuse guardrails, emphasizing policy-only outputs and explicit non-applicability zones. The framework is not a substitute for local diagnosis. Additional empirical designs are needed to separate peer effects from correlated exposure and shared shocks.

Table 6. Limitations and mitigations

Threat	*Impact*	*Mitigation*	*Boundary Cue*
Local idiosyncrasies	Lower internal validity	Sensitivity ranges	Parameter bounds
Geography transfer risk	Weaker external validity	External group holdouts	Leave-group-out
Construct miscoding	Noisy labels	IRR plus adjudication	Two annotators
Policy misuse risk	Harmful recommendations	Misuse guardrails	Policy-only outputs

Conclusion

The present study consolidates social norms and peer influence into an operational model for rural hygiene adoption, translating contextual features into intervention choices under WASH constraints. The framework couples mechanistic propositions with a coding rubric intended to support consistent reviewer annotation and to discourage single-mechanism narratives. Practical value is sharpened by explicit reference points, including logistic regression on survey features, a simple graph-metrics classifier, and generic norms messaging, which define what the model aims to improve upon. Evaluability is preserved through a programmatic cohort design using the Rural Hygiene Norms and Diffusion Cohort with grouped holdouts by entity and context and explicit audits against cross-split leakage via entity identifiers. Uncertainty quantification and reproducibility are planned via BCa bootstrap intervals (2000 resamples, stratified by external group), FDR correction, two-annotator labeling of a 15% sample, and hashed manifests for lineage. Remaining limits include geography-dependent transfer, construct mis-coding, and the absence of individual-level data or clinical impact trials.

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