Prioritizing Grievance Redressal in Community Based WASH Helpline Systems

Kshitija Tikhe, Kirti Bikram, Archana Singh, Zafar Adilov, Gularam Masharipova

Abstract: *This paper presents a theory-grounded triage framework for rural water, sanitation, and hygiene (WASH) helplines, where growing, heterogeneous grievances and limited repair capacity strain responsiveness and risk eroding trust. The operational gap is the absence of integrative prioritization that connects technical fault signatures with socio-institutional determinants while balancing urgency, population impact, vulnerability, repairability, and accountability under scarce resources. We develop a reproducible pipeline that consolidates call and SMS/app logs, maintenance records, geospatial context, and asset data; encodes a transparent weighted-sum prioritization matrix with non-compensatory safety and vulnerability gates; and elicits weights via Analytic Hierarchy Process (AHP) and Delphi, with coding reliability and data governance safeguards. Outcomes are protocol-ready rather than numeric: the framework specifies measurable indicators, benchmarking scenarios, and robustness checks, including precision, recall, F1 score (F1), Root Mean Squared Error (RMSE), time-to-resolution, cost-per-issue, and equity-disaggregated metrics, with baselines such as chronological processing and severity heuristics. The contribution is a transparent, auditable triage design that couples technical scoring with institutional mapping and participatory weighting to support explainability and fairness in resource-limited contexts. Practical deployment enables districts to prioritize repairs consistently, document accountability, and improve timeliness and equity while accommodating data noise, missingness, and capacity constraints.*

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Introduction

This section frames managerial and ethical challenges from escalating helpline grievances in rural WASH. Although digital channels widen participation, high-volume heterogeneity on pumps, latrines, and water quality overwhelms district authorities and, when responses lag or are opaque, erodes trust and equity; co-benefit or trade-off claims require smart-city evidence (Sharifi et al., 2024). Helpline-specific prioritization models reconciling urgency, population impact, and tight repair resources are scarce, and claims about sanitation's long-run effects require substantiation (Gallardo-Albarran, 2025). We propose a theory-grounded triage framework and matrix integrating public service and CRM, judged by comprehensiveness, clarity, accuracy, applicability, and adoption potential, with context-bounded generalizability.

Local Context

This study addresses burdens in WASH helplines by situating grievances within hydrogeology, seasonality, and infrastructure types. Although groundwater vulnerability and land-use dynamics vary across arid and semi-arid contexts, they shape complaint patterns (Williams et al., 2025). Long-term adaptation demands horizons responsive to coastal hazards (van Alphen et al., 2025); with effects on maintenance. High-volume, varied reports can delay repairs, misallocate scarce technician time, and erode trust. These effects warrant empirical confirmation. We map classification models, synthesize a multi-criteria triage matrix, and explicate institutional interactions. Evaluation centres on comprehensiveness, categorization clarity, prioritization accuracy, stakeholder adoption potential, and equity and vulnerability.

Research Gap

This study addresses operational bottlenecks in district WASH helplines as community grievances surge. Although fault logs capture pump failures and sanitation blockages, effective triage requires linking technical signatures to socio-institutional determinants, including trust, stigma, adaptive capacity, and reporting behaviour, which must be empirically evidenced (Azadi et al., 2025). We identify a deficit of integrative prioritization that jointly weighs urgency, vulnerability, service-impact, repairability, institutional mandate, and verification confidence. Integrating spatial-temporal validation with triage heuristics can sharpen dispatch and reduce misallocation; crowdsourced reports with geo-time checks support this claim (Barbosa et al., 2025), yet effects remain context-dependent in rural, resource-limited settings.

Study Aims

Although helpline volumes vary across districts, the study sets three aims for rural WASH helplines: characterize burden of community grievances, identify deficiencies in logging and classification, and justify a tailored multi-criteria matrix balancing urgency, impact, resource limits. We advance integrative mapping of feedback taxonomies, triage logics, and institutional responsibilities to improve responsiveness and surface trust dynamics between communities and authorities. We state testable design hypotheses: accuracy, transparency, and scalability increase, with measurable gains in framework comprehensiveness, categorization clarity, prioritization accuracy, helpline applicability, and stakeholder adoption. A multi-objective framing motivates the matrix (Azadgar et al., 2025). Efficacy requires empirical validation; pilots.

Literature Review

This review frames WASH-helpline grievance triage within resilience and environmental assessment. Although links between triage and spatiotemporal risk are sparse, flood models yield prioritization-ready risk layers (Samadi et al., 2025). Nature-based measures reshape hazards and steer repair capacity (Radu et al., 2025). Consequential life cycle assessment highlights burdens of delayed sanitation fixes, warranting weights for emissions and nutrients (Aliahmad et al., 2025). We compare logging schemas, taxonomies, and automated versus human classification against urgency, equity, and resources, and propose transparent, trust-building rules, audits, and feedback loops across low-resource community, operator, and district levels; outcomes include response time, equity, and sustainability.

Literature Review - CRM Frameworks

Table 1. Comparison of decision frameworks for urban water and resilience planning

Framework name	*Primary method*	*Application domain*	*Key objective*	*Source*
Multi-objective water allocation	Multi-objective optimization integrating recycled water	Urban water allocation	Balance shortages emissions and economic benefits	Chen et al., 2025

Participatory hydraulic-energy assessment	Participatory modelling with hydraulic and energy performance tool	Collective irrigation system management	Negotiate reliability and energy-efficiency trade-offs	Cameira et al., 2025
Community energy security appraisal	Multi-criteria AHP with spatial mapping	Rural Agri-village nexus assessment	Classify security levels to inform policy	Jean et al., 2025

This table (1) summarizes methods and domains to clarify transfer options for WASH helpline prioritization.

This section interrogates decision frameworks from urban water and resilience planning for transfer to WASH helpline grievance triage. Although multi-objective optimization formalizes urgency versus resource trade-offs, it presumes rich data and substantial computation (Chen et al., 2025). Participatory modelling improves transparency and trust, yet prioritization may drift without explicit weighting and audit trails (Cameira et al., 2025). Community-level assessment shows how to incorporate local inputs and scale across units, but adoption depends on clear categories (Jean et al., 2025). Individually modest; collectively transformative. Claims of prioritization accuracy and scalability require pilots and shadow tests against helpline backlogs.

Materials Methods

This section presents a reproducible methodology for district WASH helplines. Although volumes fluctuate, we integrate quantitative logs with stakeholder elicitation to surface tacit repair rules. We document provenance across transcripts, SMS/app reports, maintenance, GIS, and asset data; apply consent, de-identification, role-based access, and governance SOPs. The framework operationalizes urgency, population, vulnerability, downtime, repair cost, accountability, and escalation potential, using multi-criteria prioritization. Weights blend participatory inputs with AHP/Delphi (Cameira et al., 2025). Coding reliability uses kappa. Validation and sensitivity test past outcomes, fairness, and central versus decentral responses (Angelidis et al., 2025). Metrics include precision, recall, confusion matrices, time-to-resolution, pilots.

Materials Methods - Study Design

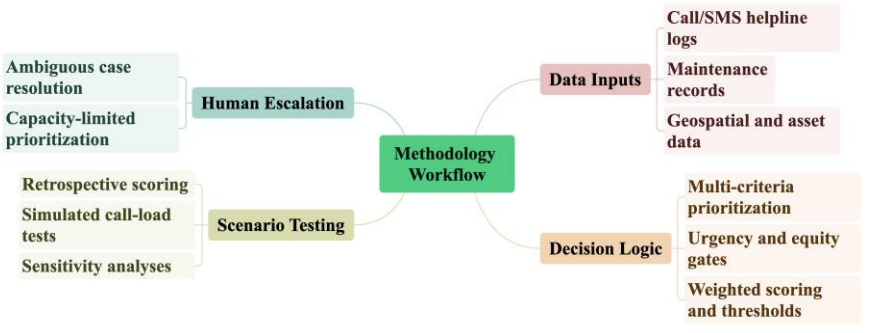

Figure 1. Integrated modelling and decision flow

This figure (1) illustrates data inputs, decision logic, scenario testing, and human escalation within the triage pipeline.

This methodology specifies a reproducible triage pipeline for district WASH helplines. Although resources are tight, prioritization uses six criteria: urgency, service impact, affected population, recurrence, cost-to-fix, institutional responsibility, with indicators. Inputs include de-duplicated call/SMS logs, field and maintenance records, and geospatial context; preprocessing standardizes codes, bounds imputations, reconciles inconsistencies, and anonymizes data. Scores map to 0-100, weights from practitioner ratings, thresholds trigger, ranking orders tickets, and escalation resolves ambiguity while capacity limits shape choices. Validation crosswalks outcomes, probes sensitivity and surge scenarios (Samadi et al., 2025), applies multi-objective balancing (Azadgar et al., 2025). Metrics track comprehensiveness, clarity, accuracy, applicability, adoption.

Materials Methods - Prioritization Matrix

$$S_i = \sum_{j=1}^{m} w_j \, x_{ij} \tag{1}$$

Equation (1) defines a composite priority score as the weighted sum of normalized criterion values, clarifying scoring, weight interpretation, and sensitivity analysis setup.

This section defines a WASH helpline prioritization matrix selecting urgency, public health risk, population affected, criticality, repair complexity, and cost/time-to-repair, normalized to 0-1 and combined with stakeholder-elicited weights; although richer multi-objective schemes exist, a weighted-sum core enables transparent, auditable, and explainable triage (Chen et al., 2025). Non-compensatory gates apply under catastrophic safety risk or when vulnerable groups are implicated, and ambiguous reports trigger conservative gating, imputation flags, and callbacks. Validation blends retrospective scoring, simulated call-load tests, and sensitivity and robustness analyses underweight-data uncertainty, with policy-aligned metrics for framework comprehensiveness, categorization clarity, and prioritization accuracy (Jean et al., 2025).

Materials Methods - Institutional Mapping

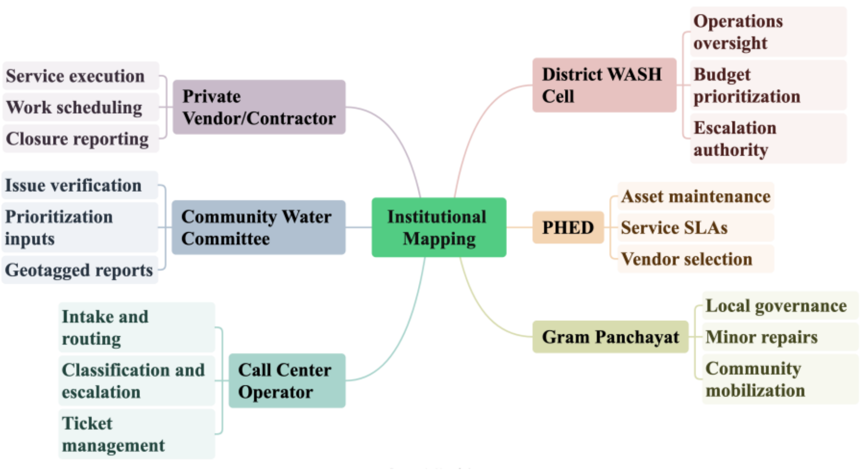

Figure 2. Stakeholder roles and institutional linkages in WASH helpline

This figure (2) depicts stakeholder authorities, data flows, and decision pathways, highlighting coordination bottlenecks and potential escalation routes across WASH helpline actors.

Table 2. Institutional roles and decision levers mapping

Institution	*Role*	*Decision scope*	*Data owned*	*Coordination notes*
District WASH Cell	Operations oversight	Budget prioritization, escalation	Call logs, action tickets	High interagency handovers to PHED
Public Health Engineering Department (PHED)	Asset maintenance	Work orders, vendor selection	Maintenance records, service SLAs	Backlogs during peak demand

Gram Panchayat	Local governance	Minor repairs, community mobilization	Meeting minutes, local registers	Informal influence on triage
Call Centre Operator	Intake and routing	Ticket classification, escalation triggers	Call audio, IVR logs	Misclassification when metadata incomplete
Community Water Committee	User representation	Issue verification, prioritization inputs	Geotagged reports, photo evidence	Validation delays without travel budget
Private Vendor/Contractor	Service execution	Work scheduling, spare parts	Job cards, invoices	Closure lags pending approvals

This table (2) lists institutions, their formal roles, decision levers, datasets under custody, and coordination notes to surface accountability and handover risks.

This section delineates formal mandates, informal decision levers, and data stewardship shaping WASH helpline performance. Although mandates seem clear, operational authority, maintenance, budgets, and data custody fragment—slowing triage and skewing equity. Map custodianship and quantify gaps via response time variance by custodian, interagency handover rates, and unresolved reports, and inventory call logs, maintenance records, geotagged reports, disbursements, under privacy. Geospatial clustering reveals overlaps and guides placement (Kapanski et al., 2025). Sea-level-rise planning informs escalation protocols (van Alphen et al., 2025). Methods combine inventories, key-informant elicitation, and metadata. Capacities inferred from self-reports validated against metrics, accountability data, and feedback loops.

Materials Methods - Evaluation Metrics

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{2}$$

Equation (2) defines RMSE as the primary scalar error for continuous-valued predictions used to compare models against operational thresholds.

This section defines an evaluation lens aligning metric choice with WASH helpline goals. Although data are noisy and incomplete, test robustness to missingness and noise. Calibrate urgency alignment, validate temporally and cross-district, benchmark against human triage, and quantify uncertainty via confidence intervals or bootstrap (Clark & Jaffres, 2025). For continuous predictions, report RMSE, residuals, subgroup bias (Clark & Jaffres, 2025). For categorical tasks, report precision, recall, F1, and threshold-optimized trade-offs under resource and social limits, plus equity via disaggregated metrics across geographies and vulnerable groups. Ground parallels and report backlog, median time-to-resolution, and cost-per-issue (Morkunaite et al., 2025); discuss accuracy interactions.

Results

This section reports evaluation constraints and the protocol-ready basis for assessing the matrix. Although no empirical WASH helpline data were accessible, we delineate measurable outputs and analytic comparators grounded in established trade-off and resilience analyses (Azadgar et al., 2025; Radu et al., 2025). No numeric outcomes are reported. The planned evaluation quantifies complaint-volume descriptors, priority-score distributions, error rates with confidence intervals, and sensitivity to weighting and crew-supply constraints, and baselines include chronological processing and severity heuristics with timeliness, response-rate, efficiency, and equity metrics. Robustness checks address missingness, noisy classification, and resource shortages; linking urgency, impact, and cost without overgeneralization.

Results - Comparative Analysis

$$PI = \frac{M_{scenario} - M_{baseline}}{M_{baseline}} \times 100 \tag{3}$$

Equation (3) defines the percent improvement calculation used to compare scenarios to baseline across all metrics.

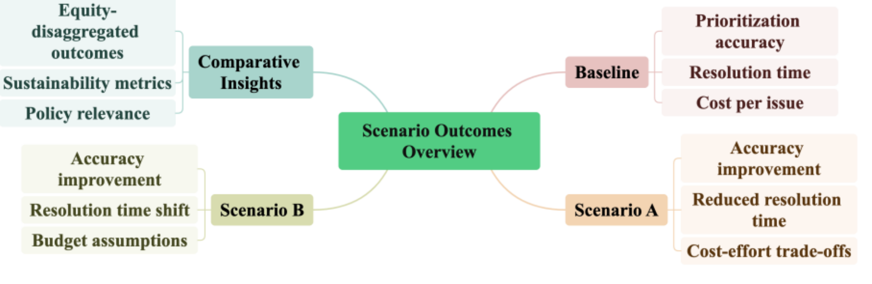

Figure 3. Comparative outcomes across scenarios

This figure (3) summarizes scenario performance and visualizes key trade-offs guiding prioritization decisions.

Table 3. Scenario outcomes versus baseline benchmarking table

scenario	*key metric 1*	*key metric 2*	*cost or effort*	*notes*
Baseline	prioritization accuracy % [95% CI]	resolution time hours [IQR]	USD per case or staff-hours	Data source and 12-month horizon
Scenario A	prioritization accuracy % [95% CI]	resolution time hours [IQR]	USD per case or staff-hours	PI relative to baseline, assumptions flagged
Scenario B	prioritization accuracy % [95% CI]	resolution time hours [IQR]	USD per case or staff-hours	PI relative to baseline, assumptions flagged

This table (3) presents a unit-explicit benchmarking template with required uncertainty fields.

This section specifies a benchmarking protocol for WASH helpline prioritization in resource-limited districts. Although data heterogeneity persists, scenarios are appraised against a baseline using unit-explicit metrics with uncertainty bounds, including prioritization accuracy (%) with 95% CI, average resolution time (hours), and cost or effort per case (USD or staff-hours). Environmental externalities will be evaluated via consequential life-cycle assessment (Aliahmad et al., 2025). Technoeconomic trade-offs and break-even thresholds follow comparative analysis benchmarks, with sensitivity to discount rate and CAPEX (Angelidis et al., 2025). Report data sources, aggregation, and imputation; flag assumption-driven results and interpret response-cost trade-offs for implementability, trust, and backlog.

Discussion

This discussion interrogates how a prioritization matrix redistributes resources in WASH helplines. Although urgency filters expedite safety risks, they may privilege users, while impact and resource constraints steer dispatch to low-cost catchments; equity can slip. Social barriers and misrecognition suppress reporting by marginalized users (Azadi et al., 2025). Automation and centralization risk skewed weights and exclude local knowledge, reinforcing asymmetries (Sovacool et al., 2025). Anticipatory governance demands stress-testing for long-term risk (van Alphen et al., 2025). Evaluate for comprehensiveness, categorization clarity, prioritization accuracy, and stakeholder acceptability. Transferability claims require empirical tests and participatory refinement with frontline users and district authorities.

Conclusion

This evaluation synthesizes the manuscript's contribution to WASH helpline grievance triage. Although data and capacity are uneven, the multi-criteria matrix enables districts to balance urgency, community impact, and constrained operations while improving transparency and trust. For designers and policymakers, it clarifies institutional interplays shaping response times and specifies accountability routines for equitable, scalable governance. It recommends continuous validation, multilingual channels, assisted callbacks, and feedback loops to reduce exclusion of marginalized users. Limits include conceptual scope and measurement uncertainty; future work should tie triage weights to groundwater indicators (Williams et al., 2025) and to multi-objective resource allocation (Chen et al., 2025).

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