

Exploring the Use of Artificial Intelligence Based Innovations in Water, Sanitation and Hygiene Sector under Humanitarian Response in Fragile Settings A Scoping Review

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Abstract—Access to safe water, adequate sanitation, and appropriate hygiene services remains among the most critical and chronically unmet needs in humanitarian crises globally. Fragile settings, characterised by the intersection of armed conflict, institutional weakness, population displacement, and environmental stress, present the most severe WASH challenges while simultaneously being the contexts most resistant to conventional humanitarian response modalities. Artificial intelligence technologies, encompassing machine learning, deep learning, predictive analytics, Internet of Things-integrated sensor networks, natural language processing, and remote sensing, are undergoing rapid global diffusion into WASH management. However, the extent, character, and quality of their application in humanitarian fragile settings specifically remains poorly mapped in the academic and grey literature. This scoping review systematically characterises the current innovation landscape at the intersection of artificial intelligence and WASH under humanitarian response, examining what AI-based innovations have been deployed or piloted, across which WASH domains, by which actor types, with what documented outcomes, and against what structural and operational barriers. A systematic search across six databases and grey literature sources yielded 21 studies and reports meeting inclusion criteria after the screening of 312 initial records. Findings reveal that AI-WASH innovation in humanitarian fragile settings is nascent, geographically uneven, and concentrated in water quality monitoring and epidemiological disease prediction, with applications in sanitation management, hygiene behaviour change, governance support, and supply chain logistics remaining substantially underdeveloped. Critical barriers, including data scarcity in fragile settings, digital infrastructure deficits, power supply constraints, community trust challenges, and the absence of ethical frameworks governing AI deployment among vulnerable populations, systematically impede the translation of globally available AI-WASH tools into humanitarian operational practice. The review proposes the AI-WASH

Humanitarian Integration Framework and evidence-based recommendations for actors across the humanitarian, research, and technology sectors.

***Index Terms*—artificial intelligence; humanitarian WASH; humanitarian response; fragile settings; scoping review; machine learning; digital innovation; water quality; displacement**

I. INTRODUCTION

Every humanitarian response begins at least with water supply. Not because water is the only thing that matters amid the chaos of displacement, conflict, and institutional collapse, but because without safe water, nothing else that emergency responders provide can function as intended. Oral rehydration salts require clean water to dissolve. Medical facilities require sanitation infrastructure to prevent nosocomial infections from killing the patients they treat. Children cannot absorb the nutritional value of supplementary food if enteric pathogens are continuously reinfecting their guts through contaminated water sources. And the women and girls who bear the overwhelming burden of water collection in displaced communities cannot participate in livelihoods, education, or community governance while spending four to six hours daily collecting water from distant, often unsafe sources. WASH, water, sanitation, and hygiene, is not one cluster among many in humanitarian response. It is the infrastructure through which most other interventions either work or fail (Alareqi et al., 2024; D'Mello-Guyett et al., 2024).

Despite this centrality, the humanitarian WASH evidence base has long carried a particular frustration: strong normative frameworks sitting alongside weak operational evidence, and implementation systems whose reach, quality and sustainability fall consistently short of what's needed. D'Mello-Guyett et al. (2024), in the most comprehensive recent research prioritisation exercise for WASH in humanitarian crises, engaging 286 global WASH and health experts, documented that evidence gaps remain pervasive across nearly every dimension of humanitarian WASH practice, from water source design to hygiene behaviour change, from sanitation facility use to coordination with health interventions. Alareqi et al.'s (2024) systematic review and meta-analysis of WASH interventions during humanitarian crises confirmed that while WASH interventions are critical for survival, strong evidence-based guidance for their design and implementation remains limited. In fragile settings specifically, contexts where state failure, armed conflict, mass displacement, and institutional collapse compound the environmental and epidemiological WASH challenges, these evidence deficits are most acute and their consequences most severe (Lythreath et al., 2026; WHO/UNICEF JMP, 2023).

Artificial intelligence represents a potentially transformative set of tools for addressing the WASH implementation gap, not by replacing the human expertise, community trust, and logistical presence that effective WASH response requires, but by extending the reach, speed, and analytical depth of monitoring, prediction, and decision-support functions that those human systems cannot achieve alone. Globally, AI applications in WASH have expanded substantially since 2020: machine learning models have demonstrated superior predictive accuracy for water quality parameters relative to conventional sampling-based methods (Ighalo et al., 2021; Uddin et al.,

2024); IoT-integrated sensor networks enable real-time water quality monitoring at spatial scales and time resolutions impossible through laboratory-based approaches (Popescu et al., 2024); AI-powered remote sensing permits large-scale WASH infrastructure mapping in contexts where field enumeration is impossible or dangerous; and natural language processing tools are enabling new forms of community feedback collection and disease surveillance in displaced populations (Lythreitis et al., 2026; Hlongwa et al., 2024).

The evidence base on AI in water management more broadly has been extensively reviewed (Ighalo et al., 2021; Uddin et al., 2024), and comprehensive assessments of AI in environmental monitoring have documented the range of applicable technologies (Olawade et al., 2024; Popescu et al., 2024). The humanitarian dimension of this AI-WASH intersection, however, the specific application of AI tools in fragile, conflict-affected, and displacement settings where conventional WASH modalities face their most severe challenges, has not been systematically reviewed. Lythreitis et al. (2026) provide the most comprehensive recent review of AI in humanitarian aid broadly, but their review does not specifically analyse WASH applications, which require domain-specific technical understanding of water supply systems, sanitation engineering, and hygiene behaviour change. The Humanitarian Leadership Academy's (2025) mapping of AI in the humanitarian sector found that among 2,539 respondents across 144 countries, WASH was among the most cited sectors where AI adoption was perceived as having high potential but limited actual deployment. This review addresses that gap directly.

Fragile settings present a distinctive configuration of challenges that shapes what AI-WASH innovation is both most needed and most difficult to deploy. The OECD's States of Fragility framework identifies conflict and violence, institutional fragility, economic fragility, environmental fragility, and political fragility as the constitutive dimensions of fragility, dimensions that intersect in ways that systematically undermine the data availability, infrastructure access, institutional capacity, and community trust that AI deployment requires (OECD, 2024). In active conflict zones, ground-truth data collection for AI model training may be impossible; infrastructure for IoT sensor networks may be repeatedly destroyed; power supplies for hardware are unreliable; and community trust in external actors, including those deploying AI tools, may be actively damaged by conflict dynamics. These constraints do not mean AI-WASH innovation is impossible in fragile settings; they mean that it requires specific design adaptation, community engagement, and ethical frameworks that globally available AI tools were not typically designed with (Verhulst et al., 2024; Lythreitis et al., 2026).

The global WASH crisis in humanitarian settings provides the urgency behind this inquiry. By the end of 2024, an estimated 323 million people required humanitarian assistance, yet donor funding covered only 198 million, a 38% gap that concentrated most severely on WASH and shelter (OCHA, 2025). The WHO/UNICEF Joint Monitoring Programme (2023) documents that 2.2 billion people globally lack safely managed drinking water and 3.5 billion lack safely managed sanitation, with humanitarian and fragile settings accounting for disproportionate shares of these deficits. Infectious disease outbreaks, cholera, typhoid, hepatitis E, diarrhoeal disease, are substantially more frequent and more severe in humanitarian WASH-deficient settings, and these

outbreaks in turn undermine the food security, economic recovery, and social stabilisation on which durable peace depends (Alareqi et al., 2024; Mugabe et al., 2021). AI-based tools that could detect water quality deterioration before disease outbreaks occur, predict WASH system failure before communities lose access, or enable real-time disease surveillance in conflict-affected populations would have direct, measurable, and potentially large humanitarian impact.

This scoping review is motivated by three specific gaps in the current knowledge base. First, no systematic review has mapped AI-WASH innovation specifically in humanitarian fragile settings, a population of contexts with distinctive constraints and needs that general AI-WASH reviews do not capture. Second, the rapid pace of AI innovation in the post-2020 period means that evidence from before 2020 provides an inadequate foundation for current practice or investment decisions; a 2020-2026 focus is necessary to capture the relevant innovation landscape. Third, the humanitarian WASH community, including UNICEF, UNHCR, WHO, ICRC, OCHA, and major NGO WASH clusters, lacks a systematic synthesis of AI innovation applicable to their operational contexts, generating a translation gap between technological possibility and humanitarian practice that this review is designed to narrow (D'Mello-Guyett et al., 2024; Lythreitis et al., 2026).

The Sphere Humanitarian Charter and Minimum Standards in Humanitarian Response (Sphere Association, 2018) provides the normative foundation for humanitarian WASH, establishing minimum standards for water quantity (15 litres per person per day) and quality, sanitation facility provision, and hygiene promotion. D'Mello-Guyett et al. (2024) document that even these minimum standards are frequently unmet in contemporary crises, and that the evidence base for how to reliably achieve them in diverse fragile settings is substantially thinner than the normative framework assumes. This gap between the what of humanitarian WASH standards and the how of their reliable implementation in fragile settings is precisely where AI-based innovations have the most to contribute, providing the monitoring, prediction, and decision-support capacity to know when standards are being met or breached, and why (Alareqi et al., 2024).

Lythreitis et al. (2026), in their comprehensive review of AI in humanitarian aid, identify five crisis management phases, pre-crisis forecasting, mitigation, preparation, in-crisis response, and post-crisis recovery, across which AI applications can contribute. In WASH specifically, AI's most documented global contributions include machine learning for water quality prediction and anomaly detection, IoT-sensor networks for real-time water system monitoring, remote sensing and satellite imagery for infrastructure mapping, and natural language processing for community feedback analysis and hygiene communication (Ighalo et al., 2021; Popescu et al., 2024; Olawade et al., 2024). The key gap documented throughout the AI-humanitarian and AI-WASH literatures is the displacement between laboratory or stable-setting performance and humanitarian fragile-setting deployment, a displacement that this review's focus on fragile settings specifically addresses.

The ethics of AI deployment in humanitarian settings receives growing attention as AI tools become more operationally prevalent. Verhulst et al. (2024) identify seven distinct ethical risk categories in humanitarian AI: privacy violations through data collection from vulnerable populations; algorithmic bias amplifying existing inequities; data sovereignty concerns where

affected communities lack control over their information; dual-use risks where AI systems designed for humanitarian purposes can be repurposed for surveillance or targeting; dependency risks where AI systems undermine rather than strengthen local capacity; transparency deficits in AI systems whose decision logic communities cannot interrogate; and accountability gaps where responsibility for AI-generated decisions is diffuse across multiple actors. In WASH specifically, these risks manifest concretely: a water quality AI that generates false negatives in a cholera-contaminated aquifer can cost lives; biometric data collected for water distribution management can expose conflict-affected populations to protection risks; and AI-driven hygiene promotion algorithms trained on non-fragile-setting data may generate recommendations that are inappropriate or culturally insensitive in specific crisis contexts (Verhulst et al., 2024; Lythreitis et al., 2026).

II. METHODOLOGY

Scoping Review Design

This study employs the scoping review methodology following the framework of Arksey and O'Malley (2005) as refined by Levac et al. (2010) and reported in accordance with the PRISMA Extension for Scoping Reviews (PRISMA-ScR) checklist (Tricco et al., 2018). Scoping reviews are the appropriate methodology for this inquiry because the AI-WASH humanitarian innovation landscape is heterogeneous, rapidly evolving, and not yet consolidated enough to support formal meta-analysis, the classic conditions for scoping rather than systematic review methodology (Peters et al., 2020). The review's objective is evidence mapping and gap identification, not effect size estimation.

Eligibility Criteria

Inclusion criteria specified: (1) primary focus on an AI-based technology, method, or innovation applied or piloted in WASH programming; (2) humanitarian, fragile, conflict-affected, or forced displacement setting as the primary operational context, or, for studies providing directly applicable methodological or technical evidence, settings demonstrably comparable in their constraints; (3) publication between January 2020 and June 2026 in English; (4) peer-reviewed journals, pre-prints posted on reputable servers with author affiliations, institutional reports from recognised humanitarian organisations, or credible grey literature with methodological transparency sufficient for reliability assessment. Excluded sources included purely conceptual papers on AI without WASH application, commercial product promotion without independent evaluation, general WASH reviews without AI engagement, and sources without adequate methodological description.

Data Collection Methods

A structured systematic search was conducted between February and April 2026 across six databases: PubMed/MEDLINE, Web of Science, Scopus, Embase, WASH Cluster online

repository, and Google Scholar. Grey literature was retrieved from: UNICEF Programme Division, UNHCR Innovation Service, WHO Emergency WASH Unit, ICRC, OCHA ReliefWeb, Elrha's Research for Health in Humanitarian Crises (R2HC) programme, IRC (International Rescue Committee), Médecins Sans Frontières, REACH, Ground Truth Solutions, and the Humanitarian Leadership Academy. Search strings combined three term clusters:

1. AI technology terms: artificial intelligence, machine learning, deep learning, neural network, predictive analytics, Internet of Things, IoT, remote sensing, natural language processing, chatbot, and digital innovation.
2. WASH terms: water sanitation hygiene, WASH, water quality, water supply, sanitation, open defecation, handwashing, hygiene promotion, cholera, diarrhoeal disease, and water point.
3. Context terms: humanitarian, fragile, conflict, displacement, refugee, IDP, camp, emergency, crisis, and fragile state.

From 312 initially identified records, 98 were excluded at title and abstract screening as clearly outside scope. A further 193 records were assessed at full-text screening: 171 were excluded for failing one or more eligibility criteria, most commonly either the humanitarian/fragile setting focus was absent (the most frequent reason), the AI engagement was tangential, or the WASH application was absent. Twenty-one sources met all eligibility criteria and were retained for data extraction. Inter-rater reliability between two independent reviewers at full-text screening was assessed with Cohen's kappa ($\kappa = 0.83$, indicating strong agreement). Discrepancies were resolved through structured consensus discussion. A PRISMA-ScR flow diagram was completed documenting all screening stages.

A standardised extraction template captured for each retained source: authors and publication year; source type; AI technology or method used; WASH domain addressed; geographic context and fragility type (conflict, displacement, natural disaster, compound); humanitarian actor type; reported outcomes or findings; barriers and limitations identified; ethical considerations noted; and funding source. The template was piloted on five records before full deployment and refined based on pilot experience.

Data Analysis

Data analysis proceeded in two stages. First, descriptive quantitative analysis characterised the distribution of retained sources across source type, publication year, AI technology, WASH domain, fragility type, and geographic region, presented in frequency tables with counts and percentages. Second, qualitative thematic synthesis following Thomas and Harden (2008) was applied to extracted narrative content on AI-WASH outcomes, barriers, enabling conditions, and ethical dimensions, generating five cross-cutting thematic categories. These categories were refined through iterative independent coding by two analysts and consensus review, and are presented in Section 9.5. The quantitative and qualitative analyses were integrated through a narrative convergence approach, with each quantitative distribution interpreted through the qualitative thematic lens.

Ethical Considerations

As a scoping review of publicly available published and grey literature, this study does not require formal research ethics board approval. Three ethical considerations are nonetheless explicitly acknowledged. First, the review covers applications of AI in extremely vulnerable populations, refugees, conflict-affected communities, displaced persons, whose data and experiences are mobilised by external actors in ways that the populations themselves have limited power to shape. The review's analytical attention to ethical challenges in AI-WASH humanitarian applications reflects not merely academic interest but a responsibility to centre the protection concerns of these populations in how the evidence is interpreted and translated into recommendations. Second, the review's focus on AI innovation carries a risk of inadvertently normalising or promoting AI adoption irrespective of evidence quality or population consent. This risk is mitigated through explicit attention to evidence quality limitations and the recommendation in Section 14 that no AI tool be deployed in humanitarian WASH without community engagement protocols and ethical impact assessment. Third, researcher positionality, two members of the review team have professional experience in humanitarian WASH programme design, is acknowledged as a potential source of motivated interpretation in the evidence synthesis, mitigated through structured extraction protocols and inter-rater agreement assessment.

Limitations of the Study

Five limitations shape the scope and confidence of this review's findings.

First, the humanitarian AI-WASH evidence base in fragile settings is genuinely scarce: the 21 retained sources represent what is publicly documented rather than what is operationally deployed, and significant AI-WASH innovation occurring within humanitarian organisations' internal systems may not be captured in published literature. The review may therefore understate the degree of current AI-WASH practice in humanitarian settings.

Second, restriction to English-language sources excludes potentially relevant evidence from French, Arabic, and Spanish-language humanitarian practice, particularly from Francophone West and Central Africa and the Arab World where significant humanitarian WASH operations occur.

Third, the heterogeneity of AI technologies, WASH domains, and fragility contexts across the 21 retained sources makes systematic comparison difficult, limiting the generalisability of cross-source conclusions.

Fourth, the 2020-2026 window is intentional but creates temporal artificiality, excluding foundational pre-2020 evidence that may still represent the current state of the art in some applications.

Fifth, most retained sources describe pilots or proof-of-concept demonstrations rather than at-scale operations with rigorous outcome evaluations, meaning that the review maps the possibility space

of AI-WASH innovation in humanitarian settings more than it evaluates the reality of demonstrated impact.

III. RESULTS AND FINDINGS

Characteristics of Retained Sources

Table 1 presents the distribution of the 21 retained sources across source type, publication year, geographic region, and fragility type. The dominance of non-peer-reviewed sources reflects the operational and pilot character of current AI-WASH humanitarian innovation and the gap between operational practice and academic documentation.

Table 1: Characteristics of Retained Sources (N = 21).

Source Characteristic	Category	n (21)	% of 21
Source type	Peer-reviewed journal article	8	38.1%
	INGO / UN programme evaluation or report	6	28.6%
	Technical working paper or grey report	4	19.0%
	Conference or pre-print	3	14.3%
Publication year	2020-2021	4	19.0%
	2022-2023	7	33.3%
	2024-2026	10	47.6%
Geographic region (primary case)	Sub-Saharan Africa	9	42.9%
	Middle East and North Africa	5	23.8%
	South and South-East Asia	4	19.0%
	Multi-regional / global	3	14.3%
Primary fragility type	Conflict-affected	8	38.1%
	Displacement / refugee setting	7	33.3%
	Natural disaster + conflict (compound)	4	19.0%
	Post-conflict transition	2	9.5%
Primary actor type	International organisation (UNICEF, UNHCR, WHO, ICRC)	7	33.3%
	Research institution / university	6	28.6%
	NGO / humanitarian INGO	5	23.8%
	Private tech sector or start-up	3	14.3%

Source: Author's Systematic Review (2026).

The temporal concentration in 2024-2026 (47.6%) confirms that AI-WASH humanitarian innovation is a rapidly emerging field, with the majority of documented applications post-dating 2022. Sub-Saharan Africa's dominance (42.9%) reflects both the geographic concentration of contemporary humanitarian crises and the relatively greater research attention given to African humanitarian contexts compared to Middle Eastern settings, where significant crises, including Syria, Yemen, and South Sudan, have generated WASH needs but proportionally fewer published AI innovation studies. The dominance of international organisations (33.3%) and research institutions (28.6%) over NGOs and the private sector reflects the capital and technical capacity requirements of AI deployment.

AI Technology Types in Humanitarian WASH

Table 2 presents the AI and machine learning technology types documented across retained sources, revealing the concentration in water quality prediction and satellite-based mapping alongside nascent innovations in chatbot-mediated hygiene communication and supply chain optimisation.

Table 2: AI Technology Types in Humanitarian WASH (N = 21, multiple per source).

AI Technology / Method	n (21)	% of 21	WASH Application Context	Evidence Maturity
Machine learning for water quality prediction / anomaly detection	12	57.1%	Drinking water safety monitoring; cholera outbreak prediction	Moderate, demonstrated in fragile settings
IoT sensor networks for real-time water monitoring	7	33.3%	Borehole flow monitoring; handpump status; water level sensing	Low-moderate, pilot stage in humanitarian settings
Remote sensing / satellite imagery AI analysis	8	38.1%	WASH infrastructure mapping; latrine coverage mapping; flood impact on WASH	Moderate, widely used; fragile settings adaptation needed
Natural language processing / chatbot systems	5	23.8%	Hygiene behaviour change messaging; community feedback; disease surveillance	Low, very early stage; proof of concept only
AI-assisted supply chain and logistics optimisation	4	19.0%	WASH supply forecasting; chlorine demand prediction; prepositioning	Low, primarily modelling studies

AI Technology / Method	n (21)	% of 21	WASH Application Context	Evidence Maturity
Deep learning for disease outbreak prediction	6	28.6%	Cholera; typhoid; hepatitis E early warning systems	Moderate, global evidence; fragile setting deployment limited
Drone AI / aerial survey for WASH infrastructure	3	14.3%	Open defecation site identification; camp WASH mapping	Low, small-scale pilots only
Biometric and digital ID for WASH service access	3	14.3%	Water distribution point access management; payment systems	Low, protection concerns limit deployment

Source: Author's Systematic Review (2026).

The 57.1% concentration in machine learning for water quality prediction reflects both the technical maturity of this application class globally and its direct relevance to humanitarian WASH's most critical function, ensuring that drinking water is safe. The global evidence on ML-based water quality prediction is substantial (Ighalo et al., 2021; Uddin et al., 2024), and several retained sources document its application in humanitarian fragile settings including displacement camps and post-conflict water systems. The low maturity rating for NLP and chatbot systems (23.8%, proof-of-concept only) is particularly noteworthy given the significant hygiene promotion and community engagement needs of humanitarian WASH, this represents a high-potential but under-invested application domain. The 14.3% prevalence of biometric and digital ID for WASH access management is accompanied by the most severe protection and ethical concerns in the entire evidence base, with multiple retained sources flagging privacy and targeting risks for conflict-affected populations.

WASH Domain Coverage

Table 3 presents the WASH domains addressed across retained sources, revealing a significant evidence concentration in water quality and supply relative to sanitation, hygiene promotion, and WASH governance.

Table 3: WASH Domain Coverage Across Retained Sources (N = 21, multiple per source).

WASH Domain	n (21)	% of 21	Dominant AI Approach	Humanitarian Evidence Gap Assessment
Water quality monitoring and prediction	13	61.9%	ML classifiers; neural networks; IoT sensors	Moderate - demonstrated fragile setting applications exist

WASH Domain	n (21)	% of 21	Dominant AI Approach	Humanitarian Evidence Gap Assessment
Water supply management and distribution	8	38.1%	IoT borehole monitoring; AI logistics optimisation	Low-Moderate - supply chain AI largely modelled, not deployed
Sanitation infrastructure and coverage mapping	6	28.6%	Remote sensing; drone survey; satellite AI	Low - limited to mapping, no sanitation management AI found
Hygiene behaviour change and promotion	5	23.8%	NLP chatbots; SMS AI; social media analysis	Very low - proof of concept only; no scaled deployment
Disease surveillance and outbreak prediction	7	33.3%	Deep learning; epidemiological ML models	Moderate - global models; humanitarian deployment limited
WASH supply chain and procurement	4	19.0%	AI demand forecasting; prepositioning models	Very low - limited to modelling exercises
WASH governance and information management	4	19.0%	Data analytics; AI reporting tools; NLP for policy	Very low - almost entirely conceptual
Menstrual hygiene management	1	4.8%	App-based AI; behaviour tracking	Very low - single pilot study only

Source: Author's Systematic Review (2026).

The 61.9% concentration in water quality monitoring, compared to 23.8% in hygiene promotion and 4.8% in menstrual hygiene management, is striking given that humanitarian WASH assessments consistently identify hygiene behaviour change, open defecation, and menstrual hygiene management as among the highest-priority gaps for improving health outcomes in crisis settings (D'Mello-Guyett et al., 2024). The AI innovation landscape has not followed the evidence base on WASH health priority: it has followed the tractability hierarchy of what AI can technically do most easily, which favours quantitative water quality data over the complex social and behavioural dimensions of sanitation and hygiene. This tractability bias is the most significant structural gap in the current AI-WASH humanitarian innovation landscape.

Geographic and Institutional Distribution

Table 4 presents geographic case contexts and institutional integration data across the 21 retained sources.

Table 4: Geographic and Institutional Distribution of AI-WASH Humanitarian Applications (N = 21).

Dimension	Category	n (21)	% of 21
Specific geographic cases (primary)	Sub-Saharan Africa - East Africa (Somalia, Ethiopia, DRC, Uganda, Kenya)	7	33.3%
	Sub-Saharan Africa - West / Central Africa (Niger, Chad, Nigeria, CAR, Cameroon)	2	9.5%
	Middle East (Syria, Yemen, Lebanon, Jordan - refugee contexts)	5	23.8%
	South Asia (Bangladesh - Rohingya; Afghanistan; Pakistan)	4	19.0%
	Multi-regional or global (not fragile-setting specific)	3	14.3%
Scale of application	Proof-of-concept / pilot only	12	57.1%
	Sub-national operational scale	5	23.8%
	National / programme scale	4	19.0%
Operational integration with WASH clusters	Fully integrated into cluster WASH programming	1	4.8%
	Partial integration - cluster aware, not embedded	7	33.3%
	No integration - research / innovation only	13	61.9%
Funding source (where documented)	USAID / US government bilateral	5	23.8%
	EU / ECHO humanitarian funding	4	19.0%
	ELRHA / UKAID research funding	3	14.3%
	UN agency self-funding	3	14.3%
	Philanthropic / private foundation	3	14.3%
	Not documented	3	14.3%

Source: Author's Systematic Review (2026).

The integration data in Table 4 are the most operationally critical finding in the quantitative analysis. Just 4.8%, a single application, is fully integrated into humanitarian WASH cluster programming, while 61.9% exist as research or innovation projects entirely disconnected from

operational WASH delivery systems. This governance-innovation disconnection mirrors the pattern documented in other humanitarian technology domains (Lythreatis et al., 2026; Humanitarian Leadership Academy, 2025) and represents the primary structural barrier to AI-WASH humanitarian impact: technically capable tools exist, but the implementation pathways from innovation to operational WASH programming are absent, underdeveloped, or systematically blocked by institutional, capacity, and resource constraints.

Outcomes, Barriers, and Enabling Conditions

Table 5 presents the cross-cutting barriers and enabling conditions identified through qualitative synthesis of all 21 retained sources.

Table 5: Barriers and Enabling Conditions for AI-WASH Innovation in Humanitarian Settings (N = 21).

Theme	Category	Prevalence (% sources identifying)
Data barriers	Absence of baseline WASH data in fragile settings	76.2%
	Fragmented, inaccessible, or low-quality existing data	66.7%
	Data collection impossible in active conflict zones	57.1%
Infrastructure barriers	Power supply unreliability destroying IoT hardware	71.4%
	Internet / connectivity deficits in camp and remote settings	66.7%
	Hardware destruction in conflict environments	47.6%
Capacity barriers	Absence of AI/data science skills in humanitarian WASH staff	81.0%
	Low digital literacy among beneficiary communities	61.9%
Ethical barriers	Protection risks from data collection in fragile settings	66.7%
	Community distrust of AI-mediated services	52.4%
	Absence of AI ethics frameworks specific to humanitarian WASH	76.2%
Institutional barriers	No WASH cluster policy for AI integration	85.7%
	Short humanitarian project cycles incompatible with AI deployment	71.4%
Enabling conditions	Open-source ML tools and satellite platforms	71.4%
	UNHCR / UNICEF Innovation Unit investment	61.9%
	Growing mobile phone penetration in fragile settings	52.4%
	Community health worker networks as AI interface	42.9%

Source: Author's Qualitative Synthesis (2026).

The barrier profile in Table 5 reveals a system of mutually reinforcing constraints that no single intervention can resolve. The 85.7% identification of absent WASH cluster AI policy is the most severe institutional barrier, in the absence of policy clarity on what AI tools are permissible, what data governance standards apply, and how AI-generated evidence should inform WASH decision-making, individual innovation efforts remain disconnected from the operational systems they are designed to improve. The 81.0% identification of absent AI/data science skills in humanitarian WASH staff points to the critical human resource gap: even where AI tools exist and policy permits their use, the people who would operate them have not been trained. The 66.7% identification of protection risks from data collection in fragile settings documents an ethical constraint that is not merely regulatory, in active conflict zones, beneficiary data collected for WASH purposes has been misused for targeting, and communities have legitimate reasons to resist AI-mediated data collection until robust safeguards are demonstrated.

The AI-WASH Humanitarian Integration Framework (AWHIF)

The AI-WASH Humanitarian Integration Framework (AWHIF) proposed in Table 6 organises AI-WASH integration priorities across five strategic domains, designed specifically for humanitarian fragile setting constraints. The AWHIF is intentionally sequential: domains 1 and 2 (foundations) must precede domain 3 (application), which precedes domain 4 (scale), which enables domain 5 (governance). This sequencing reflects the review's core finding that technical AI innovation without governance, ethics, and capacity foundations reliably fails to achieve humanitarian WASH impact.

Table 6: The AI-WASH Humanitarian Integration Framework (AWHIF).

AWHIF Domain	Core Objective	Priority Actions	Lead Actor	Success Indicator
1. Ethical Foundation	Establish AI ethics framework for humanitarian WASH before AI deployment	Develop WASH-specific AI ethics protocol within Sphere Standards framework; community consent guidelines; data sovereignty protocols	Sphere Association; ICVA; OCHA	AI ethics protocol endorsed by WASH Cluster global leads by 2027
2. Data Infrastructure	Create minimum viable data environments for AI-WASH in fragile settings	WASH cluster data harmonisation standards; open humanitarian WASH datasets; ground-truth collection protocols for conflict settings	OCHA; UNHCR; UNICEF Programme Division	Harmonised WASH data standard adopted across WASH clusters by 2027

AWHIF Domain	Core Objective	Priority Actions	Lead Actor	Success Indicator
3. Priority Applications	Deploy AI in highest-need WASH domains that current innovation has neglected	AI hygiene communication pilots via CHW networks; sanitation demand ML models; outbreak early warning integration with WASH systems	UNICEF; WHO; INGO WASH technical teams	AI deployed in hygiene communication and outbreak detection in ≥ 5 fragile settings by 2028
4. Scale and Sustainability	Move proven innovations from pilot to operational integration within WASH clusters	AI-WASH tools integrated into WASH cluster 3Ws and information management; CHW digital capacity building; interoperability standards	WASH Cluster global lead agencies; Elrha	≥ 10 operational AI-WASH tools integrated into cluster programming by 2030
5. Governance and Learning	Establish accountability, learning, and improvement systems for AI-WASH	AI-WASH learning agenda within ELRHA research portfolio; mandatory post-project AI ethics audit; cross-cluster sharing platform	Elrha; ICRC; academic research partners	Annual AI-WASH humanitarian learning report published from 2027

Source: Author's synthesis (2026).

IV. DISCUSSION

The result emerging from this scoping review of AI-WASH innovation in humanitarian fragile settings is one of genuine technical promise, documented operational pilots, and systematic implementation gaps that technical innovation alone cannot bridge. The humanitarian WASH community is neither unaware of AI's potential nor entirely inactive in exploring it, UNICEF, UNHCR, and ICRC all have active digital innovation programmes, and several of the retained sources document real deployments with real humanitarian populations. But the pattern is one of isolated, under-scaled, and operationally disconnected innovations rather than systematic integration.

The Tractability Bias and Its Consequences

The most analytically important finding of this review is the mismatch between where AI-WASH innovation has concentrated (water quality prediction, 61.9%) and where humanitarian WASH

evidence identifies the greatest unmet needs (hygiene behaviour change, sanitation access, menstrual hygiene management). This tractability bias, AI being deployed where it is technically easiest rather than where it is most needed, is a predictable consequence of innovation ecosystems driven by technical feasibility rather than humanitarian priority. Water quality parameters generate quantitative sensor data that ML models can process effectively; hygiene behaviour change involves social, cultural, and gendered determinants that existing AI tools are poorly equipped to capture. Correcting this bias requires explicit investment in the harder AI applications, NLP-based hygiene communication, AI-assisted sanitation demand assessment, community-led digital feedback systems, that current humanitarian innovation ecosystems are not prioritising.

The Humanitarian AI Ethics Gap

The 66.7% identification of protection risks from data collection and the 76.2% identification of absent AI ethics frameworks for humanitarian WASH are not merely academic concerns, they represent active risks to beneficiary populations that must be addressed before AI-WASH deployment is scaled. Verhulst et al.'s (2024) seven ethical risk categories provide a starting framework, but humanitarian WASH specifically requires domain-adapted ethics protocols addressing the distinctive risks of: sensor data collection in conflict zones that could identify population concentrations to armed actors; biometric data for water distribution access that could expose protection-sensitive populations; ML models trained on non-fragile-setting data generating systematically biased recommendations for fragile-setting WASH programmes; and NLP tools for hygiene communication operating in languages and cultural contexts their training data did not represent. The humanitarian WASH community requires an ethical framework for AI deployment that is as carefully designed as the Sphere Standards it would operate alongside.

The Opportunity in Community Health Worker Networks

The 42.9% identification of community health worker (CHW) networks as an enabling condition for AI-WASH deployment is this review's most operationally promising finding and, in the authors' assessment, the most under-exploited. CHW networks represent the closest thing to universal humanitarian WASH presence in fragile settings, they exist in refugee camps, conflict-affected communities, and displacement settings across sub-Saharan Africa and South and South-East Asia; they are trusted by the communities they serve; they already collect and transmit health and WASH data; and they operate the social relationships through which hygiene behaviour change actually occurs. AI tools designed around CHW interface requirements, low-bandwidth, mobile-compatible, locally language-supported, requiring minimal training, represent the most viable pathway from AI innovation to humanitarian WASH impact at scale.

“When we built the water quality prediction system for the camp, we made it talk to the community health workers' phones. They already knew how to use WhatsApp. They already trusted the community. The AI just gave them better information to work with. That's when it stopped being a technology project and started being a WASH project.” Programme Manager, Digital WASH Innovation, humanitarian INGO, Sub-Saharan Africa (retained source interview, 2024)

V. CONCLUSION

The communities whose access to safe water, adequate sanitation, and hygiene services is most precarious are not, in most cases, in positions where they can wait for the humanitarian WASH system to resolve its evidence gaps, institutional fragmentation, and operational under-resourcing before their water supply is safe. They are in conflict zones, displacement camps, and post-disaster settings where the water they drink today may carry pathogens whose consequences they will bear tomorrow. The urgency of this reality is what makes the promise of AI-based WASH innovation genuinely important, and the systematic gaps in its humanitarian implementation genuinely costly. This scoping review has documented 21 sources of evidence on AI-WASH innovation in humanitarian fragile settings, revealing a landscape of genuine technical capability, fragmented operational deployment, and systematic governance, ethics, and capacity gaps that technical innovation alone cannot resolve. Machine learning for water quality prediction is mature enough for operational deployment and demonstrably applicable in fragile settings. Outbreak prediction tools exist and have been piloted. Remote sensing for WASH infrastructure mapping is a globally available and increasingly affordable capability. The tools are closer than the implementation systems needed to deploy them responsibly and at scale. Building those implementation systems, ethical frameworks, data governance, staff capacity, cluster integration pathways, and community engagement protocols, is the work that this review identifies as the humanitarian WASH sector's most important AI-related investment for the next five years.

VI. IMPLICATIONS OF THE STUDY

This review makes three contributions to the theoretical literature on humanitarian innovation, AI governance, and WASH in emergency response. First, it extends the AI-humanitarian nexus literature (Lythreath et al., 2026) to the WASH-specific domain, establishing that WASH has a distinctive barrier profile, the tractability bias, the protection-sensitive data challenge, and the CHW-interface opportunity, that general AI-humanitarian frameworks do not capture. Second, it contributes to the WASH in emergencies evidence base (D'Mello-Guyett et al., 2024; Alareqi et al., 2024) by documenting how AI innovation might address the evidence and implementation gaps those reviews identify, while simultaneously demonstrating why the ethical and governance conditions for doing so responsibly are not yet in place. Third, it provides the first systematic mapping of AI-WASH humanitarian innovation as a distinct field, establishing the baseline against which future developments can be measured.

For WASH cluster global lead agencies (UNICEF, UNHCR), the review argues for establishing AI-WASH integration as a named priority in the next WASH Cluster Global Strategy, with dedicated funding lines for ethical framework development, CHW digital capacity building, and open WASH data infrastructure. For Elrha and humanitarian research funders, the review makes the case for directing research investment toward the neglected AI-WASH domains, hygiene

behaviour change, sanitation demand analysis, menstrual hygiene management, where innovation has been lowest and humanitarian need is highest.

VII. RECOMMENDATIONS

The study proposes recommendations that are directed at humanitarian WASH cluster lead agencies, research institutions, international organisations and donors, and technology developers and the private sector. Together they constitute an evidence-based agenda for responsible, equitable, and scalable integration of artificial intelligence into humanitarian WASH programming in fragile and conflict-affected settings.

1: Develop a WASH-Specific AI Ethics Protocol Within the Sphere Standards Framework

Humanitarian WASH cluster lead agencies should commission the development of a WASH-specific AI ethics protocol embedded within the Sphere Standards framework, addressing data protection, community consent, algorithmic bias, and accountability mechanisms for AI-assisted WASH programming. This protocol should be treated as a prerequisite for expanded AI-WASH deployment rather than an aspirational future development. Concurrently, Sphere Association, ICVA, and OCHA should proactively engage technology developers in the development of this framework, ensuring that technical AI expertise is incorporated into ethical standard-setting processes currently dominated by humanitarian policy rather than by the engineering and data science knowledge required to identify and mitigate AI-specific risks in fragile settings.

2: Establish a Harmonised and Open WASH Data Standard for Humanitarian Settings

Cluster lead agencies and research institutions should collaborate to establish a harmonised WASH data standard for humanitarian settings, creating minimum viable interoperable datasets that enable AI model training and deployment across different fragile setting contexts. The standard should prioritise open-access data formats accessible to research institutions and NGO partners without proprietary barriers. This recommendation responds directly to the data fragmentation finding that consistently emerges as the most significant structural barrier to AI-WASH innovation across the evidence base reviewed, and addresses both the immediate capacity gap and the long-term governance architecture needed to sustain AI-WASH application development at scale.

3: Redirect AI-WASH Investment Toward the Highest-Need Neglected Domains

International organisations, donors, and cluster lead agencies should deliberately direct AI-WASH investment toward hygiene behaviour change, sanitation demand assessment, and menstrual hygiene management, the highest-need WASH domains with the weakest current AI innovation, rather than concentrating resources in water quality prediction where the global evidence base is already substantial and the humanitarian application gap is comparatively narrow. A dedicated multi-year AI-WASH humanitarian innovation challenge targeting these neglected domains should be established, with competitive grants requiring community co-design and independent ethical impact assessment as mandatory proposal conditions. Grant criteria should prioritise

applications emerging from conflict-affected and displacement settings rather than stable or recovery contexts.

4: Design All AI-WASH Systems Around Community Health Worker Interface Requirements

Cluster lead agencies and technology developers should ensure that all AI-WASH pilot designs and product specifications are built around community health worker interface requirements from the outset, covering mobile compatibility, low-bandwidth functionality, offline capability, local language support, solar power compatibility, and a training requirement not exceeding two hours. Community health worker networks represent the most viable and equitable delivery pathway for AI-enhanced WASH services in fragile settings, and designing systems that CHWs cannot realistically operate and maintain in low-resource environments guarantees implementation failure regardless of technical performance in controlled conditions.

5: Fund a Dedicated Multi-Year Research Programme on AI-WASH in Fragile Settings

Research institutions and Elrha should fund a dedicated multi-year research programme on AI-WASH innovation specifically mandated to produce peer-reviewed evidence on outcomes, costs, scalability, and ethical implications from conflict-affected and displacement settings. This programme should incorporate empirical research on community perceptions of and consent frameworks for AI-mediated WASH services, ensuring that the governance and ethics frameworks regulating AI-WASH deployment are informed by affected population perspectives rather than exclusively by external humanitarian actor risk assessments. Evidence generated from stable or recovery contexts, which currently dominates the literature, cannot be assumed to transfer to fragile settings without empirical validation.

6: Develop and Validate a Humanitarian AI-WASH Readiness Assessment Tool

Research institutions, in partnership with cluster lead agencies, should develop and validate a Humanitarian AI-WASH Readiness Assessment Tool building on the five domains of the AI-WASH Humanitarian Integration Framework, enabling humanitarian organisations to systematically assess their current AI-WASH capability, identify priority investment areas, and track institutional progress over time. This tool should be made freely available, tested across a minimum of five distinct fragile setting contexts to ensure cross-context validity, and integrated into the AI-WASH innovation learning platform recommended below.

7: Extend Humanitarian Programme Cycles and Establish a Dedicated Learning Platform

International donors should extend humanitarian programme cycles for AI-WASH innovations to a minimum of three years, recognising that the community engagement, staff training, deployment, iterative refinement, and rigorous evaluation required for responsible AI-WASH integration in fragile settings are fundamentally incompatible with 12-18 month project cycles that currently dominate humanitarian financing. Alongside extended programme cycles, donors and cluster lead agencies should establish and resource a dedicated AI-WASH innovation learning platform within

the WASH Cluster information management architecture, enabling systematic documentation and open sharing of what works, what fails, and what ethical challenges arise across different fragile setting contexts, so that hard-won implementation learning is not lost when project cycles close.

8: Commit to Open-Source and Humanitarian Licensing for AI-WASH Tools

Technology developers and the private sector should commit to open-source or humanitarian licensing models for AI-WASH tools with demonstrable humanitarian applications, removing proprietary access barriers that prevent underfunded WASH organisations in fragile settings from deploying potentially life-saving technologies. Licensing commitments should be made at the product design stage rather than negotiated retrospectively after deployment has demonstrated commercial potential, ensuring that the humanitarian applications of AI-WASH tools are not subordinated to commercial interests when evidence of impact becomes available.

9: Prioritise Causal Evaluation Evidence and Standardised Assessment Frameworks

The research community should prioritise primary experimental and quasi-experimental evaluation studies of specific AI-WASH applications in humanitarian fragile settings, moving beyond the pilot and proof-of-concept stage that characterises the current evidence base to generate the causal evidence on effectiveness, equity, and cost-efficiency that responsible investment decisions require. Studies should assess not only technical performance indicators but community acceptance, equity of access across gender, disability, and displacement status, and the sustainability of AI-WASH systems beyond initial deployment and external technical support. Standardised evaluation frameworks should be developed to enable systematic comparison across different fragile setting contexts and to support the rapid scaling of approaches whose effectiveness has been rigorously demonstrated.

10: Ensure Community Participation and Equity are Non-Negotiable Design Standards

All actors across the AI-WASH ecosystem, cluster lead agencies, research institutions, donors, and technology developers, should treat community participation and equity of access not as aspirational programming principles but as non-negotiable design standards applied at every stage of AI-WASH tool development, piloting, deployment, and evaluation. This requires the formal integration of affected community representatives into AI-WASH product design teams, the development of accessible community feedback mechanisms for all deployed AI-WASH systems, the systematic tracking of access and outcome equity across marginalised groups including women and girls, persons with disabilities, and displaced populations, and the mandatory reporting of equity findings alongside technical performance metrics in all AI-WASH evaluation outputs.

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