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Diagnosing water infrastructure underutilization: a planning framework for behavioral risk, smart monitoring, and SDG 6.1 alignment

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ABSTRACT

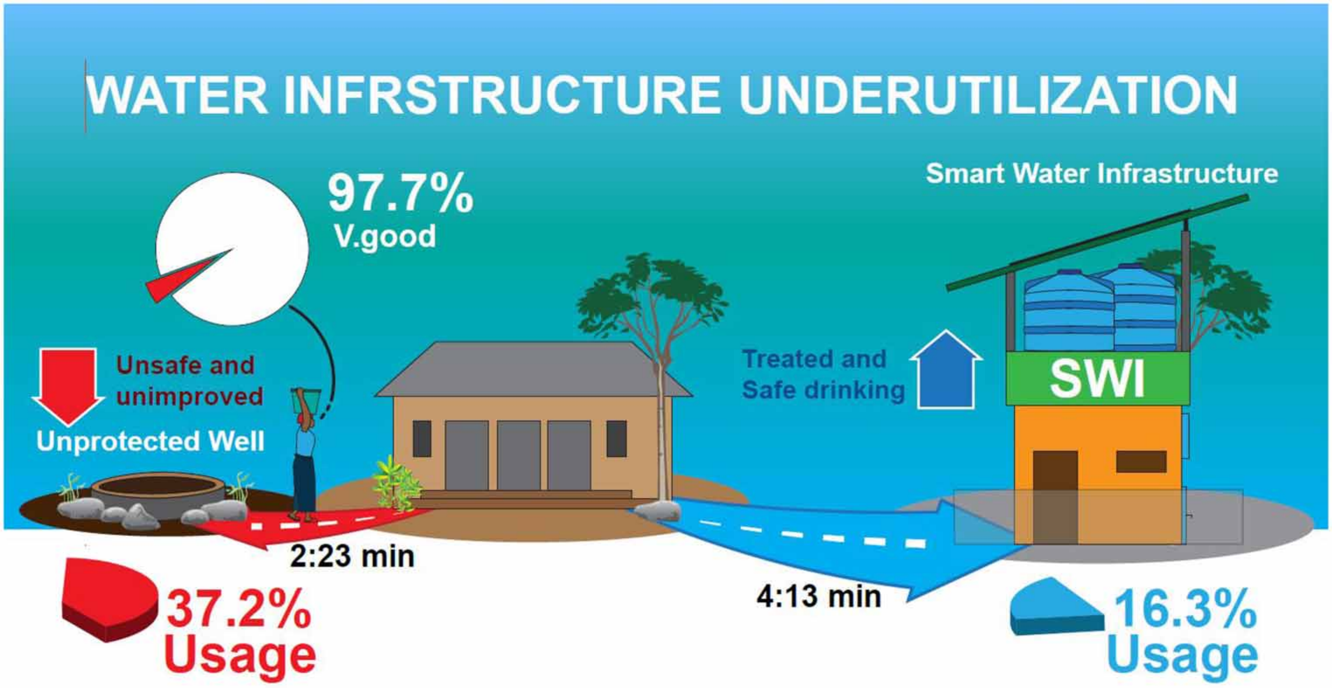
Water infrastructure in resource-scarce settings often remains underutilized despite being technically sound and publicly funded. This study introduces the Water Infrastructure Underutilization Principle, a behavioral insight developed through an integrated research design. Using household surveys ($n = 86$), GIS walking times, IoT flow data, and clinic records, we investigate adoption behavior (household uptake of smart water infrastructure (SWI) for drinking) in a Nigerian community classified as water poor. Despite access to treated water from a SWI, initially offered for free, only 16.3% of households used the SWI, while 97.7% rated existing sources 'very good', including unprotected wells. IoT monitoring over 168 days recorded usage at 1.52% of the system's design capacity. Walking time to the SWI averaged 4 min 13 s, versus 2 min 23 s to alternatives. Proximity-effect modeling shows that each additional minute of walking reduced the odds of SWI adoption by 48% (AOR $\approx$ 0.52). These findings reveal a threshold dynamic shaped by perception, proximity, and the absence of perceived water-related health risks from existing sources. The study proposes behaviorally informed planning reforms, offering a transferable framework for diagnosing underutilization risk and supporting SDG 6.1 by aligning delivery with community uptake.

Key words: Nigeria, proximity, SDGs, smart monitoring, sustainable water infrastructure, water infrastructure underutilization

HIGHLIGHTS

- Integrates IoT data, household surveys, and clinic records to assess adoption behavior.
- Finds that the distance and perceived safety of existing sources reduce uptake of SWI, even when water is treated and free.
- Identifies behavioral variables that can strengthen infrastructure planning and siting decisions.
- Provides a transferable framework to support SDG 6.1 in comparable settings.

GRAPHICAL ABSTRACT



1. INTRODUCTION

Under the United Nations' stewardship, the international community is committed to achieving Sustainable Development Goal (SDG) 6.1, which targets universal and equitable access to safe, affordable drinking water by 2030 (United Nations 2015). Despite progress, substantial challenges remain, particularly in Sub-Saharan Africa, where pronounced disparities in water infrastructure development and sustainability persist (Andres *et al.* 2018a; Adeniran *et al.* 2021; Adeoti *et al.* 2023). In these regions, the absence of rigorous planning and assessment standards, which are commonly employed in developed countries, impedes the effective implementation and long-term sustainability of water infrastructure projects (Adshead *et al.* 2019; Adeoti *et al.* 2024b).

Water systems in developed countries exemplify robust infrastructure planning processes, where pre-construction and resilience assessments are used to manage health, safety, economic risks, and interdependencies (Fekete 2011; Thacker *et al.* 2017). High-income countries such as Canada, the Netherlands, and Germany have developed infrastructure criticality criteria to optimize outcomes (Robert 2003; Vrijling *et al.* 2004; Fekete 2011). Despite the importance of these assessments, developing countries like Nigeria often lack such evaluations, leading to resource wastage, recurrent project failures, and widespread underutilization (Adeniran *et al.* 2021; Adeoti *et al.* 2024a, b, 2025). A practical implication is that expanding service access alone does not guarantee household uptake; even technically compliant systems can remain underutilized once delivered.

In Nigeria, most water infrastructure projects, including boreholes and standpipes, are delivered by non-governmental organizations, government agencies, and water authorities, with funding derived from public budgets and international aid (Andres *et al.* 2018b; Adeniran *et al.* 2021; Adeoti *et al.* 2023). Over 60% of the rural population relies on boreholes for daily drinking water (Akpabio & Takara 2014; UNICEF & WHO 2021). Household piped connections are rarely feasible in rural and peri-urban areas due to prohibitive capital and maintenance costs, making communal systems such as boreholes and standpipes the predominant service model. While these systems address immediate shortages, they frequently neglect long-term sustainability (Bonsor *et al.* 2015; Whaley & Cleaver 2017; Adeniran 2022; Adeoti *et al.* 2023). A critical gap in pre-construction planning and post-construction monitoring has exacerbated the short-term orientation of these projects, limiting their long-term effectiveness (Abbas *et al.* 2016; George-Williams *et al.* 2024; Adeoti *et al.* 2024b). Consequently, assessing the performance of communal infrastructure over time is vital. Accordingly, this study evaluates a communal smart water kiosk designed for water-poor rural settings as a realistic alternative to household piped connections.

Infrastructure underutilization is an insufficiently documented issue affecting communal water systems, despite its major implications for sustainability and investment efficiency (Adeoti *et al*. 2025). In this study, underutilization is defined as the suboptimal use or neglect of functional infrastructure, including in communities officially classified as suffering extreme water poverty under international benchmarks such as UNESCO, UN-Water, and the WHO/UNICEF Joint Monitoring Programme (UNESCO World Water Assessment Programme *et al*. 2023; United Nations Children's Fund & World Health Organization 2024). While these benchmarks provide a useful basis for global comparison (e.g., source type, distance, availability), they do not capture the local behavioral dynamics that determine use. Although underutilization has been recognized in other infrastructure sectors (Uzgör & Şengür 2022; Qiao *et al*. 2024), its manifestations in the water sector remain conceptually underdeveloped and empirically underinvestigated. This study addresses that gap by providing the first detailed analysis of the behavioral, spatial, and planning dimensions of water infrastructure underutilization in a resource-scarce, high-need setting.

The chronic underutilization of water infrastructure undermines cost recovery, economies of scale, and project sustainability, slowing progress toward SDG 6.1. In Nigeria and across Sub-Saharan Africa, project justifications frequently rely on generalized data that lack the granularity to capture local behavioral dynamics shaping uptake and long-term use (Hope *et al*. 2020; Adeoti *et al*. 2024a). Similar limitations have been recognized globally, where studies emphasize the importance of modeling context-specific drivers to align infrastructure with demand. Carrying-capacity analysis in Xi'an aligns services with projected need (Yang *et al*. 2019). In Pakistan, geographic information system (GIS)-guided siting in Lahore and MODIS monitoring in Gilgit-Baltistan improve system placement and adaptive management (Zafar *et al*. 2021; Siddiqui *et al*. 2023). In the Upper Indus Basin, geomorphological assessment shows how physical setting and governance shape feasible pathways (Ahtisham *et al*. 2024). Cross-domain evidence on parameter sensitivity reinforces the value of predictive approaches that incorporate local conditions (Ahamad *et al*. 2020). Together, these insights highlight the importance of demand-aware planning that moves beyond coverage typologies to address behavioral and spatial determinants of uptake.

Understanding why communities facing extreme water poverty underutilize infrastructure requires attention to behavioral, socioeconomic, and operational factors alongside entrenched planning norms. Frameworks such as RANAS (Risk, Attitudes, Norms, Abilities, and Self-Regulation) support post-construction behavior change (Mosler 2012) but are not suited to pre-construction, where predictive rather than corrective assessment is needed. These models depend on extensive post-construction data and prolonged engagement, making them impractical for early planning. In the absence of predictive and pre-construction assessment methods, projects often rely on generalized metrics such as JMP classifications (e.g., 'improved' and 'unimproved'), which overlook user behavior and may lead to limited uptake. To address this gap, this study examines behavioral thresholds identifiable before deployment, offering perception-informed, spatially sensitive planning heuristics that can refine water poverty assessments and support progress toward SDG 6.1 in comparable contexts.

2. METHODOLOGY

Figure 1 provides an overview of the methodology process, summarizing the key steps that are elaborated in the subsections that follow.

2.1. Theoretical framework

This study integrates four perspectives to examine water infrastructure sustainability and underutilization in resource-scarce settings. Systems theory views infrastructure as a complex adaptive system shaped by technical, institutional, and community dynamics (Meadows 2008; Ostrom 2009); sustainability theory emphasizes long-term viability and the interdependence of environmental, financial, and governance factors (United Nations Human Settlements 2006; Harrington 2016); the theory of planned behavior (TPB) links household adoption to attitudes, perceived behavioral control, and subjective norms (Ajzen & Schmidt 2020); and diffusion of innovations theory explains adoption through perceived advantage and contextual fit (Sahin 2006; Kaminski 2011). These lenses were operationalized across a multi-phase research program in Nigeria, refined through successive phases, and culminating in the identification of underutilization as a critical challenge. The sequence of phases underpinning the methodological approach is detailed in Supplementary Section S1 and Figure S1.

2.2. Study design

This study investigates the underutilization of smart water infrastructure (SWI) in a high-need Nigerian community, focusing on the behavioral and spatial dynamics influencing household adoption. Using a mixed-methods design, it combines

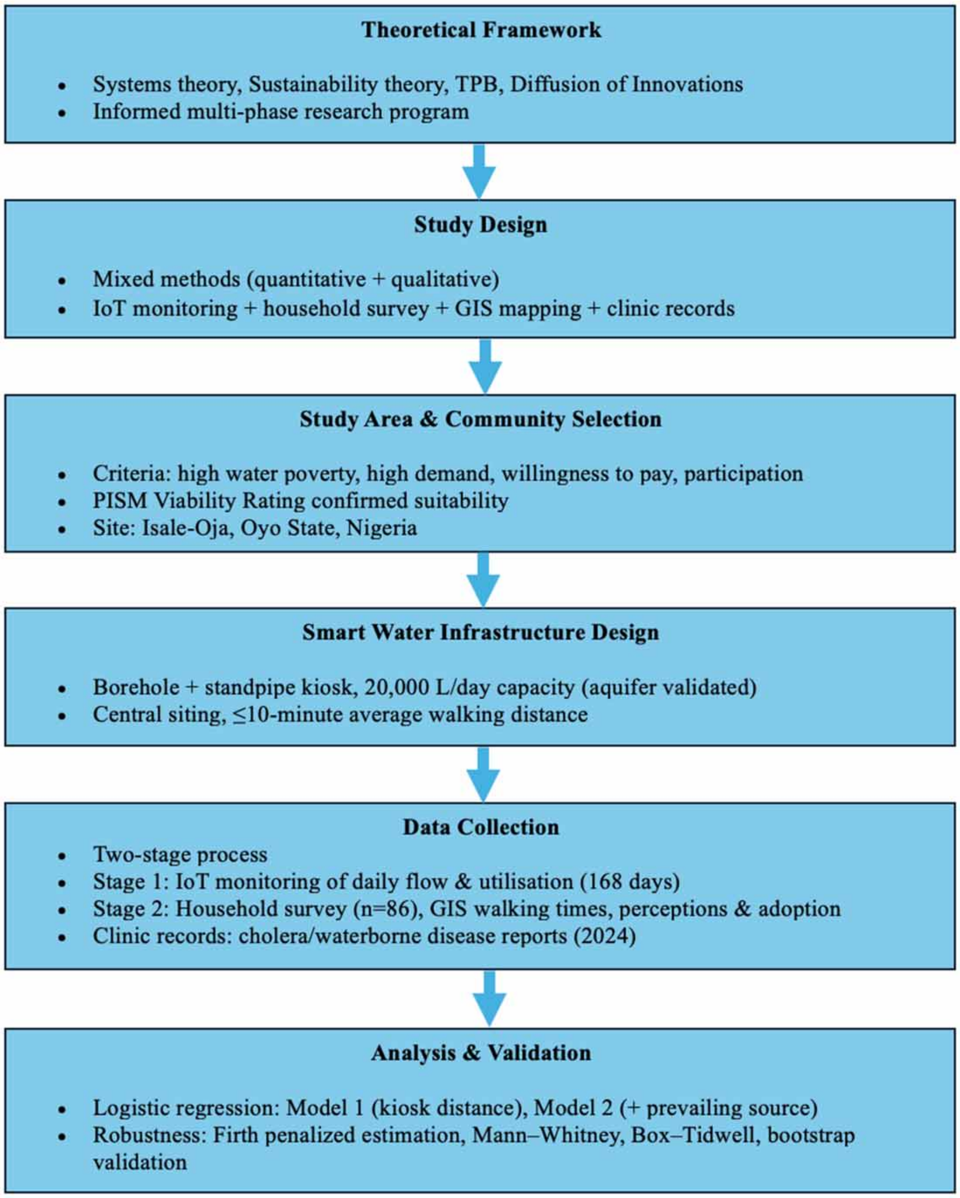


Figure 1 | Methodology process flowchart.

quantitative monitoring of infrastructure usage with qualitative assessments of community perceptions and access barriers. Usage was tracked through IoT-based monitoring of the SWI, while additional data sources included a household survey on perceptions, behavior, and socio-demographic factors; GIS-based estimates of walking time to water sources; and clinical records of waterborne illness from a local facility. Together, these sources support a multi-dimensional analysis of household adoption. The SWI evaluated incorporates a borehole and standpipe, reflecting the communal service model predominant in rural and peri-urban Nigeria, where household piped connections are rarely feasible due to capital and maintenance constraints. Framing the analysis around SWI thus captures the practical infrastructure realities of water-poor communities and enables an evaluation directly relevant to their predominant service conditions.

2.3. Study area

The Isale-Oja community in Oyo State, Nigeria (Latitude: 7.6301; Longitude: 3.8462) was selected as the study site due to documented water access challenges, infrastructure needs, and alignment with national and international benchmarks for water poverty, based on assessment criteria from the WHO/UNICEF Joint Monitoring Programme (JMP) and the Nigeria Bureau of Statistics' Multiple Indicator Cluster Survey (National Bureau of Statistics & UNICEF 2022; UNESCO World Water Assessment Programme *et al*. 2023). Among 1,696 communities mapped through field visits, Isale-Oja was identified as one of the most water-poor (Adeoti *et al*. 2024a). A location-viability rating using the Predictive Iterative Sustainability Model (PISM) confirmed its suitability for SWI deployment (Adeoti *et al*. 2024b). Selection criteria included high water poverty rates, demand, willingness to pay, and community participation. Reliance on unhygienic and unprotected wells that were visibly discolored, malodorous, and unsafe further illustrated its status as an exemplar of rural water poverty. Although no laboratory testing was conducted in this phase, field observations confirmed these wells would not meet drinking water standards. This targeted selection anticipated high utilization of the installed infrastructure, addressing immediate need, maximizing impact, and supporting long-term sustainability.

2.4. Infrastructure design

The SWI in Isale-Oja was centrally located to ensure accessibility, averaging a 10-min walk for intended users. Designed with a daily capacity of 20,000 L, it targeted the community's estimated demand of 15,090–19,345 L/day, derived from a household survey of 86 households conducted by Adeoti *et al*. (2024b). Aquifer testing confirmed sufficient groundwater yield to meet demand.

Design and placement were guided by a community-level viability rating using the PISM (see Supplementary material). This assessment involved structured community engagement to evaluate demand, willingness to pay, source preferences, and receptiveness to improved services, while introducing the smart water solution and its intended health benefits. These activities served both to determine feasibility and to raise community awareness in advance of deployment. Further details on the scientific basis of PISM, the engagement process, and the architectural design are provided in Supplementary Section S2 and Figure S2.

2.5. Data collection

Data collection was conducted in two stages to thoroughly assess both the quantitative and qualitative aspects of the water infrastructure's utilization.

2.5.1. Stage 1: Infrastructure utilization monitoring

The utilization rate of the smart water kiosk was continuously monitored using an IoT device that recorded the total water dispensed daily. This IoT setup, as described in Adeoti *et al*. (2025), incorporates advanced processes for data anomaly detection, data validation, and data integrity. Over the observation period, the total water dispensed was computed as

$$T = \sum_{n=1}^{N} (\mathrm{WC}_n + \mathrm{RW}_n + \mathrm{NRW}_n)$$

where N is the number of days; WCn is water credit (free water) on day n; RWn is revenue water (sold) on day n; and NRWn is non-revenue water on day n. Equivalently, period totals satisfy $T = \mathrm{WC} + \mathrm{RW} + \mathrm{NRW}$. The kiosk utilization rate was then

$$\text{Utilization rate} = \frac{T}{N \times \text{Daily capacity}}$$

2.5.2. Stage 2: Utilization investigation

This stage involved a comprehensive household survey to examine utilization of the SWI and reasons for non-utilization. Survey items covered reasons for non-use, alternative water sources for general and drinking purposes, perceptions of water quality and health outcomes, and household adoption. Clinical data from local clinics were also integrated to triangulate community perceptions against documented cases of water-related disease. In addition, GIS technology was used to map household locations relative to the kiosk and alternative sources, providing precise measures of physical accessibility.

The household sample size was calculated using Cochran's formula with finite population correction and adjusted for clustering using a design effect:

$$n = \frac{z^2 \times p \times (1-p)}{E^2} \Big/ \left[1 + \left(\frac{z^2 \times p \times (1-p)}{E^2} - 1\right) \Big/ H\right] \tag{1}$$

$$\mathrm{DE} = 1 + (b-1) \times \mathrm{ICC} \tag{2}$$

where $Z = 1.96$ (95% confidence), $p = 0.5$ (maximum variability), $E = 0.05$ (margin of error), H is the total number of households, b is the average households per house, and ICC is the intra-cluster correlation coefficient. Based on community mapping by Adeoti *et al.* (2024b), the Isale-Oja population was estimated at 1,900 people, with an average of 4.5 persons per household and 3 households per dwelling. Although the use of averages may reduce household-level variability, it provides a consistent and transparent basis for estimating survey requirements. Applying these values yielded a minimum requirement of 80 houses, and 86 houses were surveyed to strengthen representativeness and allow for potential non-response. Further details are provided in Supplementary Section S3.

The household dataset included:

1. *Perceived quality*: Household perceptions of SWI, boreholes, protected wells, unprotected wells, and sachet water, rated on a four-point Likert scale (Very Good, Good, Poor, Very Poor).
2. *Health perception*: Self-reported perceptions of water-related health risks, recorded as a binary variable (Yes/No) with qualitative descriptions of perceived safety.
3. *Distance*: Walking time in minutes to SWI and alternatives, measured using GIS mapping.
4. *SWI usage*: Binary adoption variable (Yes = 1, No = 0).
5. *Clinic data*: Records from the Oyo State Ministry of Health (January–December 2024) on cholera and other water-related diseases, used to compare household perceptions with clinical evidence.

2.6. Method of data analysis

The choice of analytical relationships was guided by the distribution of responses. All survey variables were first tabulated. Perceived water quality (97.7% 'very good') and health safety perception (100% 'no issues') showed extreme homogeneity. To quantify this lack of variation, the coefficient of unalikeability was computed:

$$U = 1 - \sum_{i=1}^{k} p_i^2$$

where p_i is the proportion in the ith response category. Values below 0.10 denote near-zero variance. Quality ($U = 0.05$) and safety ($U = 0.00$), therefore, provided no information for inferential analysis and were treated as baseline contextual constants. Supplementary Table S1 reports household-level covariates and their treatment in the analysis.

Inferential modeling: Because distance to the kiosk exhibited a meaningful spread while quality and safety did not, we modeled household adoption (Use = 1 vs 0) with a parsimonious binary logistic regression using walking time to the SWI (minutes) as the primary predictor, with a sensitivity model that additionally included walking time to the household's prevailing source. The parsimonious primary model included the only variable exhibiting adequate spread, walking time to the kiosk (minutes):

$$\mathrm{logit}\,[P(\mathrm{Use} = 1)] = \beta_0 + \beta_1\,\mathrm{Distance}_{\mathrm{SWI}}$$

A sensitivity model added walking time to the household's current water source to test robustness while respecting the events-per-variable rule (14 adoption events → ≤2 predictors). Models were fitted with maximum likelihood; McFadden's R^2 assessed explanatory power and likelihood-ratio tests compared nested models. Penalized (Firth) logistic estimates were generated to check for small-sample bias; coefficients differed by <5%, confirming stability. All analyses were conducted in R Statistical Software (R Core Team 2023) using the base package stats and the logistf package for Firth's bias-reduced logistic regression (Heinze & Schemper 2002).

Targeted robustness checks. To confirm that the proximity effect reflected the data structure rather than sample idiosyncrasy, three checks were applied:

1. *Model-free contrast*: Mann–Whitney U with Hodges–Lehmann median difference and Cliff's δ.
2. *Functional-form test*: Box–Tidwell for logit linearity, with a pre-specified $1 - df$ flexible alternative if required.
3. *Bootstrap validation*: 1,000 replicates reporting ROC AUC, Precision–Recall AUC, Brier score, and calibration intercept/slope.

Full procedures and outputs are in Supplementary Section S5 and Tables S2A and S2B. This stepwise approach preserved statistical power despite limited adoption events, adjusted for ceiling effects in perception variables, and yielded interpretable effect-size estimates for the proximity gradient.

2.7. Methodological rigor and adaptation

This study adhered to stringent methodological standards to ensure the reliability, validity, and scientific integrity of data collection, analysis, and interpretation. The methodological approach builds on prior peer-reviewed studies that documented water infrastructure challenges, sustainability modeling, and smart-system evaluation in the Nigerian context (Adeoti *et al*. 2023, 2024a, b, 2025). These published works provide an established foundation, while the present study extends the evidence base by focusing specifically on the behavioral and spatial dynamics of infrastructure underutilization.

3. RESULTS AND DISCUSSION

3.1. Infrastructure utilization: operating at only 1.52% of designed capacity

Household demand for improved water services in Isale-Oja was estimated at 15,090–19,345 L/day, with 103 of 422 households projected to adopt the SWI system (Adeoti *et al*. 2024b). The kiosk was therefore designed with a 20,000-L daily capacity, equivalent to expected utilization rates of 75.5% at the lower estimate and 96.7% at the upper. However, actual usage during the first 168 days post-launch fell far short (Figure 2). The kiosk dispensed an average of 304 L/day, representing 1.52% of its design capacity.

As shown in Figure 2, usage was modestly higher in the first month, peaking at 5.05% when water was provided for free. As described in Section 2.3 (Study area), willingness to pay was assessed during pre-construction, and households were engaged and informed that payment would commence after a 1-month introductory free period to support ongoing maintenance. Despite this arrangement, usage during the free month remained low and declined further once payment began. This persistent divergence between projected and observed demand establishes the underutilization problem that subsequent results examine through household source choices, perceived quality and safety, clinic records, and measures of access.

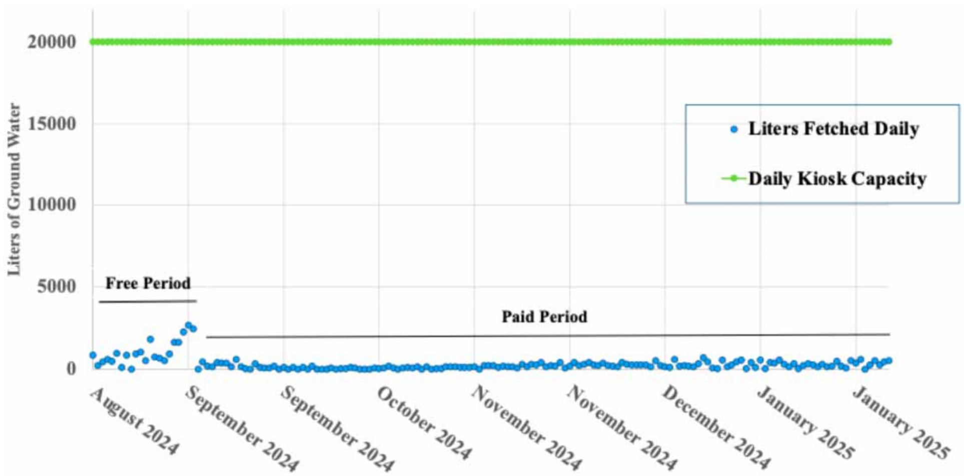


Figure 2 | Time series scatter plot of daily water kiosk utilization compared with designed capacity.

3.2. Evidence of persistent underutilization from longitudinal assessment

Consistent underutilization, as observed in this study, has important implications for the sustainability of water infrastructure. This finding is reinforced by longitudinal evidence from a 1,095-day evaluation of SWI in Nigeria (Adeoti *et al.* 2025). Despite continuous monitoring across both rainy and dry seasons and under conditions of free and paid access, utilization in that study peaked at only 7.63% of design capacity. Underutilization was therefore evident in both studies, even where technical adequacy and water demand were established. This convergence of evidence demonstrates that the challenge is recurrent and extends beyond technical sufficiency, highlighting its significance for communities experiencing extreme water poverty.

3.3. Alternative water sources utilization in Isale-Oja

Only 16.3% of 86 surveyed households in Isale-Oja used SWI, indicating a strong preference for alternatives.

3.3.1. Non-drinking water sources

- 55% relied on unprotected wells, alone or with other sources.
- 42% used protected wells.
- 19% depended on boreholes.
- 52% supplemented with rainwater.
- 0% used SWI for non-drinking purposes.

Totals exceed 100% because households often used multiple sources (see Supplementary Figure S2).

3.3.2. Drinking water sources

- 42% used protected wells.
- 37.2% relied on unprotected wells.
- 22.1% depended on boreholes.
- 12.8% used sachet water.
- 16.3% used SWI, alone or in combination.
- 87.2% supplemented with rainwater, reflecting its widespread use for drinking. Availability is seasonal, peaking in June–August, declining by September, and with dry conditions from November. Although the observation period captured only the late rainy season through the dry season (August–January), SWI underutilization remained consistently low across these months (Figure 2), a pattern also reported in a prior longitudinal study in Nigeria (Adeoti *et al.* 2025).

As with non-drinking purposes, percentages exceed 100% due to multiple-source use; combinations are detailed in Supplementary Figure S3.

3.4. Drinking water quality perception and health safety

3.4.1. Self-reported perceptions

Survey data from Isale-Oja showed that 100% of respondents reported no water-related health issues, affirming their sources, including unprotected wells (37.2% of households), as safe, despite their classification as unsafe and unimproved by national (NSDWQ 2015) and international (World Health Organization 2022) standards.

3.4.2. Quality perception by source type

- SWI, boreholes, protected wells, and sachet water: 100% of respondents rated these sources as 'very good'.
- Unprotected wells: 94% rated 'very good' and 3% 'poor', despite their observed condition as unhygienic and unimproved, highlighting the gap between community perception and technical assessment. This perception of safety, reinforced by the absence of illness, reduces incentives to adopt SWI and underscores the role of perception in underutilization. Supplementary Figure S4 illustrates this uniformity in perceived quality across sources.

3.5. Clinic-validated outcomes

Clinic records from January to December 2024, covering all 33 local government areas in Oyo State, indicated that only 26 of the state's 3,259 communities reported cholera or other water-related diseases. Isale-Oja was not among them (see

Supplementary Table S3). While this absence of documented illness aligns with community perceptions of safety, it does not confirm that water sources are risk-free. Health surveillance systems are prone to underreporting, limited care-seeking, and diagnostic constraints. Nonetheless, the consistency between local perceptions and available clinical data reinforces the behavioral finding that, in the absence of visible or reported illness, communities deem it unnecessary to shift from existing familiar sources. This alignment helps explain why technically improved infrastructure, such as the SWI, may be underutilized even when available and accessible.

3.6. Distance analysis between households, alternative water sources, and SWI

GIS mapping showed the following average walking distances in Isale-Oja:

- *Alternative sources:* households were, on average, 2 min 23 s away, with the farthest up to 6 min.
- *SWI:* households were, on average, 4 min 13 s away, with the farthest up to 10 min.

Although the SWI's average distance complied with the United Nations standard for basic water service accessibility, defined as a 30-min round trip (Cassivi *et al.* 2018; WHO 2019), households preferred closer alternatives, typically saving less than 2 min irrespective of source safety. Supplementary Figure S5 illustrates the average distances to drinking water sources.

3.7. Proximity-effect modeling

Building on the descriptive profile, two logistic regression models tested whether walking time explains SWI uptake (Table 1):

Model 1 (primary): distance to the SWI only. Each additional minute reduced adoption probability by 48% (adjusted odds ratio (AOR) = 0.52, 95% CI 0.34–0.81, $p = 0.003$; McFadden $R^2 = 0.11$).

Model 2 (sensitivity): distance to the SWI plus distance to the prevailing source. The SWI effect remained stable (AOR = 0.55, 95% CI 0.36–0.84), while the added covariate was not significant (AOR = 1.60, $p = 0.19$; McFadden $R^2 = 0.12$). Firth-penalized estimates differed by <5%, confirming stability.

Robustness checks gave consistent results: adopters lived closer to the SWI by a median of 3 min (Mann–Whitney $U = 195.0$, $p < 0.001$), the effect was linear (Box–Tidwell $p = 0.930$), and validation showed good discrimination (ROC AUC = 0.81; PR-AUC = 0.37) with acceptable calibration (Brier = 0.112). Full details are in Supplementary Section S5 and Tables S2A and S2B.

Interpretation. The results indicate that where existing sources are perceived as safe and satisfactory, walking time to the SWI appeared to be the key determinant of adoption. Prevailing sources averaged 2.38 min away compared with 4.21 min for the SWI, and even this modest difference suppressed uptake. Thus, when familiar sources are closer and perceived as risk-free, new infrastructure, even if treated, reliable, and initially free, is unlikely to displace established behavior.

The behavioral sequence aligns with the TPB, which explains adoption through attitudes, subjective norms, perceived behavioral control, and intention. Households displayed favorable attitudes toward familiar sources, a shared norm of perceived safety, and lower perceived behavioral control because longer walking distances constrained access to the SWI. Intention was not directly measured, though a brief rise in usage during the free water month may indicate temporary

Table 1 | Logistic regression of smart water kiosk adoption ($N = 86$)

Predictor	β (SE)	AOR (95% CI)	p
Primary model			
Walking time to kiosk (min)	−0.65 (0.22)	0.52 (0.34–0.81)	0.003
Constant	0.30 (0.58)	1.36 (0.44–4.21)	0.598
Sensitivity model			
Walking time to kiosk (min)	−0.60 (0.22)	0.55 (0.36–0.84)	0.006
Walking time to current source (min)	0.47 (0.35)	1.60 (0.80–3.20)	0.190
Constant	−1.02 (1.14)	0.36 (0.04–3.35)	0.370

Note: AOR, adjusted odds ratio; McFadden $R^2 = 0.11$ (Model 1) and 0.12 (Model 2).

willingness to adopt. Behavior was observed as adoption (use vs non-use). This operationalization of TPB provides empirical grounding for the Water Infrastructure Underutilization Principle and suggests that even technically sound infrastructure may remain underutilized when planning does not account for these behavioral drivers.

3.8. Introducing the Water Infrastructure Underutilization Principle

This study introduces the Water Infrastructure Underutilization Principle, which substantiates established evidence on the influence of distance while contributing new behavioral insight into why technically viable infrastructure remains unused in high-need settings. *The principle holds that in water-poor communities where households perceive their existing water sources as satisfactory and free of health risks, even marginal differences in accessibility can lead to sustained non-use of new infrastructure, regardless of its technical or financial superiority*.

3.8.1. Empirical grounding of the principle

As shown in Section 3.6, households in Isale-Oja favored slightly closer sources that were perceived as safe, even when the SWI offered treated water at no cost. The absence of reported illness, reinforced by clinic records, further illustrates how a lack of perceived harm weakens incentives to switch. These findings empirically substantiate the *Water Infrastructure Underutilization Principle* and highlight a gap in current water poverty assessments, underscoring the need for eligibility frameworks that integrate proximity, perception, health outcomes, and affordability.

3.8.2. Implications for water poverty assessment

Global monitoring frameworks such as the WHO/UNICEF Joint Monitoring Programme (JMP) provide standardized water access metrics, including availability, accessibility, quality, and safely managed classifications (United Nations Children's Fund & World Health Organization 2024). These benchmarks are widely used by funders and agencies to track progress toward SDG 6.1. However, they overlook behavioral dimensions. In Isale-Oja, for instance, unprotected wells deemed unsafe under national (NSDWQ 2015) and international (World Health Organization 2022) standards were nonetheless rated 'very good' by households, illustrating how perception can override technical classification.

To address this, we propose expanding water poverty assessments to include the following behaviorally predictive variables:

- *Perceived quality and satisfaction:* how households themselves rate or feel about the water they use (e.g., 'very good', 'safe', 'satisfactory'), even when this diverges from national or international safety standards (Satterthwaite & Mitlin 2013).
- *Health outcomes* linked to water use, validated against clinic records where possible (Hunter *et al.* 2010).
- *Proximity of existing sources*: even small distance differences significantly affect adoption (Burt & Ray 2014; Okumah & Yeboah 2020).

Integrating these behavioral predictors with assessment metrics or reporting, such as JMP, can improve diagnostic accuracy, help ensure interventions reflect community realities, and increase the likelihood of sustained adoption. This combined framework may offer greater practical value for planners and funders and provide a more effective pathway for accelerating progress toward SDG 6.1.

3.9. Recommendations and future research

This study's findings demonstrate that adoption is strongly conditioned by proximity and perceptions of safety, which collectively underpin the Water Infrastructure Underutilization Principle. Building on this insight, we propose actionable recommendations for practitioners and identify priorities for future research.

3.9.1. Recommendations

- *Integrate behavioral predictors into planning and assessment.* Infrastructure placement should apply eligibility criteria that account for local behavioral thresholds such as perceptions of safety, proximity advantages, and affordability, together with refined water poverty assessments that include satisfaction with existing sources, distance to alternatives, and clinic-reported health outcomes. These additional metrics can improve predictive accuracy and ensure that infrastructure delivery aligns not only with need but also with the likelihood of sustained adoption.

- *Institutionalize utilization monitoring.* Governments and funders should require post-construction monitoring using smart technologies to detect underutilization and implement corrective action as new systems are rolled out.

3.9.2. Future research

- *Cross-context validation.* Replicate the analysis in different rural and peri-urban settings in Nigeria and across Sub-Saharan Africa to examine whether the Water Infrastructure Underutilization Principle holds in varied contexts. Such studies should test whether the principle consistently explains patterns of non-use where existing sources are perceived as satisfactory and safe, as well as in cases where accessibility disadvantages or other behavioral factors contribute to underutilization.
- *Examine behavioral dynamics.* Investigate how perceptions of source safety, proximity advantages, willingness to walk to a point source, social norms, health outcomes, technical performance (e.g., taste, flow rate, reliability), and affordability interact in shaping adoption. This evidence can be used to develop adoption-risk indices that make adoption likelihood measurable and comparable across settings. These indices should be validated through longitudinal tracking to understand adoption trajectories over time.

3.10. Study limitations

A key limitation was the community-wide perception bias: 97.7% of households rated their sources, including unprotected wells, as 'very good', and none reported health concerns. This uniformity limited the use of perceived quality and safety as explanatory variables. To address this, we (i) treated these perceptions as contextual constants, (ii) focused the logistic model on walking distance, which showed sufficient variation, and (iii) triangulated results using Firth-penalized estimation (<5% coefficient drift) and 168 days of IoT flow data, which recorded usage at 1.5% of design capacity. Another limitation was the absence of laboratory testing of alternative sources such as unprotected wells, which restricts the ability to confirm definitively that sources perceived as safe were in fact unsafe. To address this, we assumed that these sources were unsafe based on their appearance, including discoloration, odor, and unhygienic surroundings. Future research should incorporate laboratory testing to triangulate perceptions of safety with measured contaminants and, where feasible, link results to health outcomes through longitudinal tracking. A further constraint was the small number of adoption events (14 of 86), which limited model complexity and explanatory power. To mitigate this, we applied robustness checks (non-parametric contrast, functional-form test, and bootstrap validation; see Supplementary material). While the findings may not be statistically generalizable, the behavioral pattern, methodological approach, and underutilization principle are conceptually transferable to other resource-scarce settings facing similar challenges.

4. CONCLUSION

This study introduces the Water Infrastructure Underutilization Principle as a novel behavioral explanation for why technically sound and sustainably managed water systems may fail to achieve impact in water-poor settings. Drawing on household survey data, IoT flow monitoring, clinic records, and logistic modeling, the analysis shows that despite access to treated water initially offered for free, only 16.3% of households adopted the new system, representing 1.5% of design capacity. Each additional minute of walking time reduced adoption odds by 48%. The findings highlight a threshold dynamic: when health risks are not perceived and existing sources are considered satisfactory, even if unsafe, spatial convenience and behavioral inertia outweigh the benefits of improved infrastructure. To address this challenge, the study proposes planning-stage reforms that incorporate behavioral predictors into eligibility criteria, including perceptions of quality, source proximity, and willingness to transition. It further calls for refinements to water poverty assessments by integrating variables that better forecast actual uptake. The Water Infrastructure Underutilization Principle thus provides a practical diagnostic tool for agencies to anticipate where perceptual and spatial factors may constrain adoption. Aligning interventions more closely with community realities can reduce resource waste, strengthen sustainability, and advance progress toward SDG 6.1 in comparable water-poor settings.

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ETHICAL CONSIDERATIONS

This study was conducted in strict adherence to the ethical guidelines and standards set forth by the University of Technology Sydney, with ethics approval granted under UTS HREC REF NO. ETH23-7980.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information. Additional datasets generated during the study, including anonymised field survey, are available from the corresponding author upon reasonable request.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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