Digital Twins for Urban WASH System Optimization and Resilience Assessment

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Abstract: *This study presents a decision-oriented conceptual model for urban water, sanitation, and hygiene (WASH) digital twins that support performance and resilience decisions under incomplete data and fragmented governance. The central gap addressed is the absence of an operational model that maps context and governance constraints to decisions through propositions that can be evaluated, rather than asserted. The approach specifies a three-layer architecture (operational state, model, decision), encodes entities and intervention links using a knowledge graph, and fixes constructs through a coding rubric aligned to pressure prediction, event detection f1, and decision support uptime percent. A programmatic cohort validation plan is defined using grouped holdouts by entity and context, train-only preprocessing with entity ID leakage audits, baseline comparisons (LSTM, isolation forest, static calibrated hydraulic model, threshold alarm rules), and uncertainty reporting via BCa bootstrap 95% confidence intervals with 2000 resamples; robustness is stress-tested under missing-sensor slices, seasonal drift, and resource and climate constraints. No empirical results are reported here, but the framework provides auditable decision objects and a falsifiable evaluation protocol intended to*

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guide utility operations and asset managers when selecting interventions under affordability and capacity limits.

Keywords: Urban WASH Digital Twins, SCADA and IoT Data, Hydraulic Decision Support, Non-Revenue Water Metrics, Utility Resilience Planning, Monsoon Flood Risk, Grouped Holdout Validation, Evidence Provenance

Introduction

Urban water, sanitation, and hygiene (WASH) digital twins are framed as operational decision-support models embedded in city digital infrastructures. Recent syntheses indicate that the urban digital twin (UDT) landscape remains fragmented, with uneven standards and limited cross-domain integration (Wu & Guan, 2024). Fig. (1) situates the contribution in an urban WASH operations scene where sensing, inference, and operator decisions interact. Positioning WASH twins within this broader UDT context clarifies required interfaces, governance constraints, and the practical limits of data completeness (Wu & Guan, 2024).

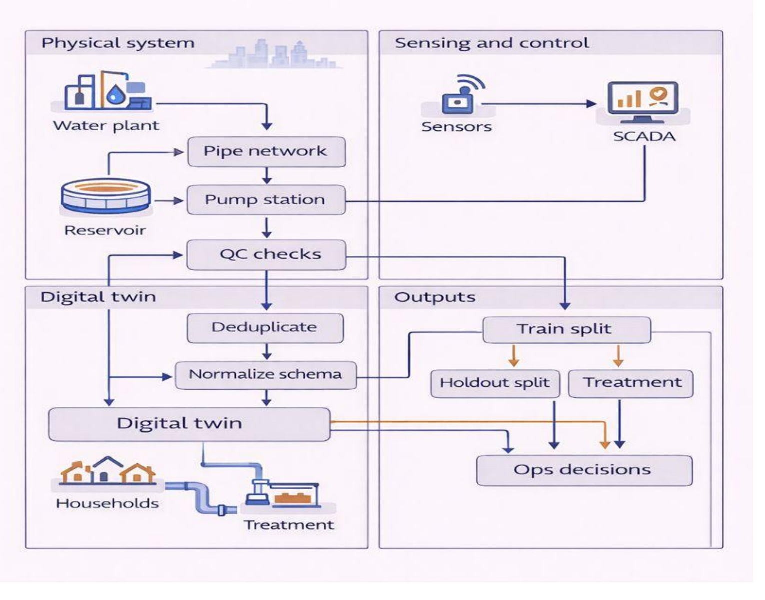

Figure 1. *Urban WASH digital twin domain scene*

AI-enabled analytics can improve fault detection and service continuity, yet water systems carry cyber-physical and governance risks that require caution

(Richards et al., 2023). The analysis develops a conceptual model by synthesizing urban digital twin ideas and adapting them to WASH operations. For research design transparency, the approach defines core constructs, states propositions linking context to decisions, and provides a coding rubric and cohort validation plan. Scope is utilities operating with fragmented data; outputs target policy and planning rather than site-specific engineering (Richards et al., 2023).

Background and Related Foundations

Urban digital twins increasingly require federation across heterogeneous assets and jurisdictions, a need articulated in Internet of Federated Digital Twins architectures that emphasize hierarchical interactions among physically separated twins (Yu et al., 2024). Baselines for resilience-oriented digital twins include lifecycle frameworks, such as urban flooding platforms spanning preparedness to recovery, that structure end-to-end decision support (Ge & Qin, 2025). Fig. (2) positions these baselines alongside cross-sector architecture surveys and comparison axes relevant to critical infrastructure deployments (Al-Shetwi et al., 2025; Alturki et al., 2024; Ardebili et al., 2024; Liu et al., 2024).

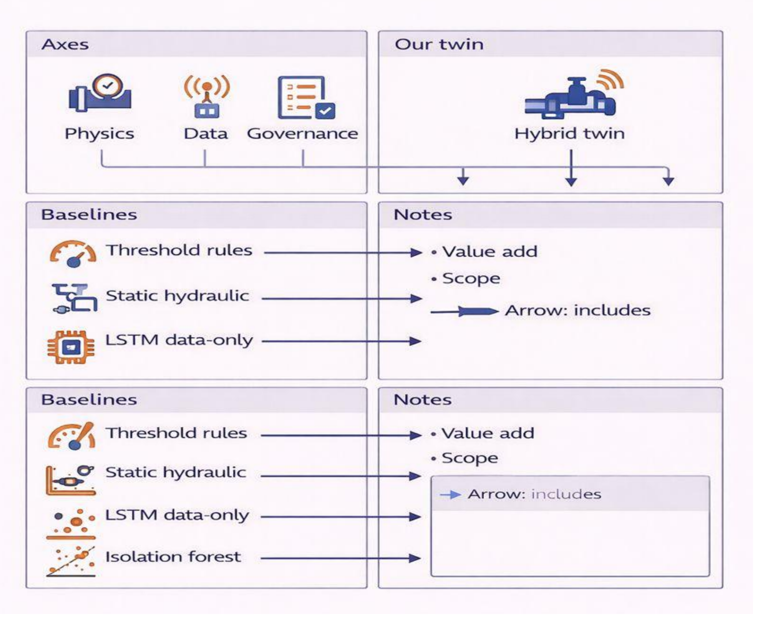

Figure 2. *Baselines landscape and comparison axes*

Smart-city implementations often fail under fragmented data, governance constraints, and privacy or security risks, which motivates explicit treatment of information stewardship in urban analytics (Gilman et al., 2024; Mupfumira et al., 2024). Equity and citizen-centric concerns further shape what constitutes actionable utility from digital twins, particularly where digital divides persist (Bittencourt et al., 2025). Evidence corpus integrity is supported by drawing on structured syntheses and SWOT-based assessments that make selection logic explicit; the inclusion rules for additional sources are not reported here (Greif et al., 2024).

Urban WASH Digital Twins: Baselines and Gaps

Urban WASH digital twins (DTs) require baseline comparators that reflect prevailing utility automation practice while exposing structural limitations. Table (1) compares four baseline approaches, their roles in the analysis, and the corresponding gaps for Urban WASH DT decision support. Regarding baselines, recurrent LSTM forecasting and isolation forest anomaly detection capture temporal patterns but do not enforce hydraulic consistency or rich operational context, consistent with limitations noted for data-driven automation in wastewater control (Cairone et al., 2024).

Physics-based calibration remains an essential reference point, yet its data and calibration burden can be misaligned with fragmented municipal records and intermittent sensing. Simple threshold-based alarm rules offer transparent deployment, but high false alarms can erode trust and mask rare but consequential events. Stormwater monitoring reviews emphasize that current practices often underestimate impacts and motivate harmonized e-monitoring for operation and maintenance (Suits et al., 2023); this gap framing supports DT designs that couple mechanistic constraints with context-aware detection.

Table 1. Baselines and gaps summary

Baseline Approach	***Role In Study***	***Key Gap For WASH DT***	***Citation Anchor***
LSTM temporal model	State forecasting baseline	No physics constraints	Ref (Sathupadi et al., 2024)

Isolation forest	Anomaly baseline	Weak context modeling	Ref (Jameil & Al-Raweshidy, 2025)
Hydraulic calibrated model	Physics baseline	Data and calibration burden	Ref (Cairone et al., 2024)
Threshold alarm rules	Rule baseline	High false alarms	Ref (Richards et al., 2023)

Programmatic Cohort Evidence: Source Provenance and Inclusion Rules

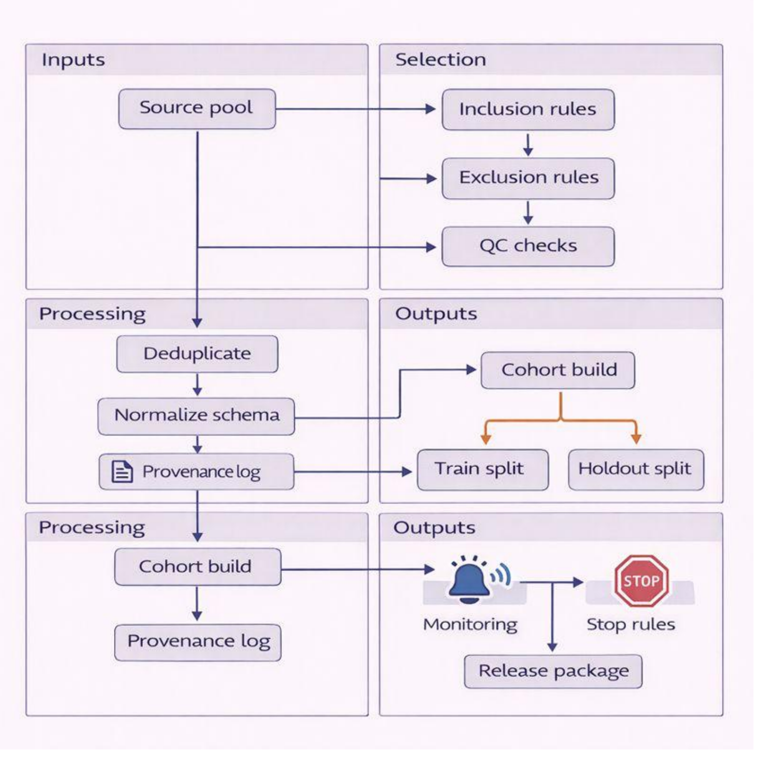

Figure 3. *Cohort selection and provenance flow*

Programmatic cohort construction required explicit provenance cues and inclusion rules to keep the evidence corpus integrity auditable at platform scale. Table (2) summarizes five source types, spanning public aggregate WASH statistics, utility KPI catalogs, SCADA/IoT telemetry, digital twin frameworks, and stormwater e-monitoring, with corresponding inclusion rules (non-personal city aggregates, operationally interpretable KPIs, persistent entity IDs, decision-support relevance, and OandM decision tables) and integrity controls (range checks, QC blockers, leakage prevention, and manifest hashing) (Bellini et al., 2024).

Fig. (3) details how provenance cues are carried through selection so that each cohort record can be traced from source category to the applied integrity control. The flow mirrors middleware practices that log sensor collection and verify deployment configurations, which reduces mismatch between data acquisition and operational use (Langer et al., 2024). Evidence corpus integrity is therefore treated as a gating criterion, but handling of incomplete or ambiguous provenance metadata is not reported here and should be specified during cohort validation.

Table 2. Cohort provenance and inclusion rules

Source Type	***Provenance Cue***	***Inclusion Rule***	***Integrity Control***
Public aggregate WASH stats	Published indicator ladders (Richards et al., 2023)	City-level, non-personal	Range checks
Utility KPI catalogs	Utility KPI mapping (Richards et al., 2023)	Operationally interpretable	QC blockers
SCADA/IoT telemetry	Smart-city IoT streams (Gilman et al., 2024)	Entity IDs present	No cross-split leakage
Digital twin frameworks	Urban DT scope cues (Wu & Guan, 2024)	Decision-support relevant	Hash manifests
Stormwater e-monitoring	Harmonized e-monitoring (Suits et al., 2023)	OandM decision tables	Lineage manifests

Conceptual Framework

The conceptual framework specifies a decision-oriented digital twin (DT) architecture for urban WASH operations under fragmented observations. It separates (i) an operational state layer that aggregates available measurements and proxies, (ii) a model layer that estimates pressures and detects events, and (iii) a decision layer that selects actions subject to constraints. The design adapts DT decision-support patterns that integrate data-driven components with explicit domain knowledge (Ieva et al., 2024). Decision objects are defined as auditable recommendations.

A knowledge graph is used to encode entities (assets, locations, sensors), their relations, and the mapping from inferred DT states to candidate interventions, enabling consistent construct labelling across utilities. This structure also supports evaluability by linking each proposition to observable indicators such as pressure prediction mae, event detection f1, and decision support uptime percent. The mechanism assumes that missing-data patterns are not fully adversarial; when reporting gaps dominate, graph-based reasoning may still propagate bias, a limitation noted in related DT prototypes (Ieva et al., 2024).

Key Constructs and Definitions for SCADA and IoT Data

Conceptual precision is enforced by fixing constructs, units of analysis, and coding cues used to label Supervisory Control and Data Acquisition (SCADA) and IoT evidence in the WASH digital twin (DT) rubric. Table (3) defines Pressure Prediction MAE (Mean abs pressure error, meters), Event Detection F1 (0-1 on burst/contam events), and Decision Support Uptime (percent DT availability), plus the Grouped Holdout split rule and the BCa Bootstrap CI (95% CI; 2000 resamples) with associated coding cues. Definitions follow monitoring DT patterns (Jameil & Al-Raweshidy, 2024, 2025).

Latency-sensitive streaming is treated as a property of the sensing pipeline rather than a model metric, because delayed telemetry can mimic anomalous behavior and distort event labels. Fig. (4) summarizes the construct hierarchy and unit of analysis used when mapping raw sensor streams to monitoring, detection, and decision-support outcomes. The same coding cues should be applied when interpreting reports of low-latency digital twin monitoring architectures and their response-time trade-offs (Jameil & Al-Raweshidy, 2024).

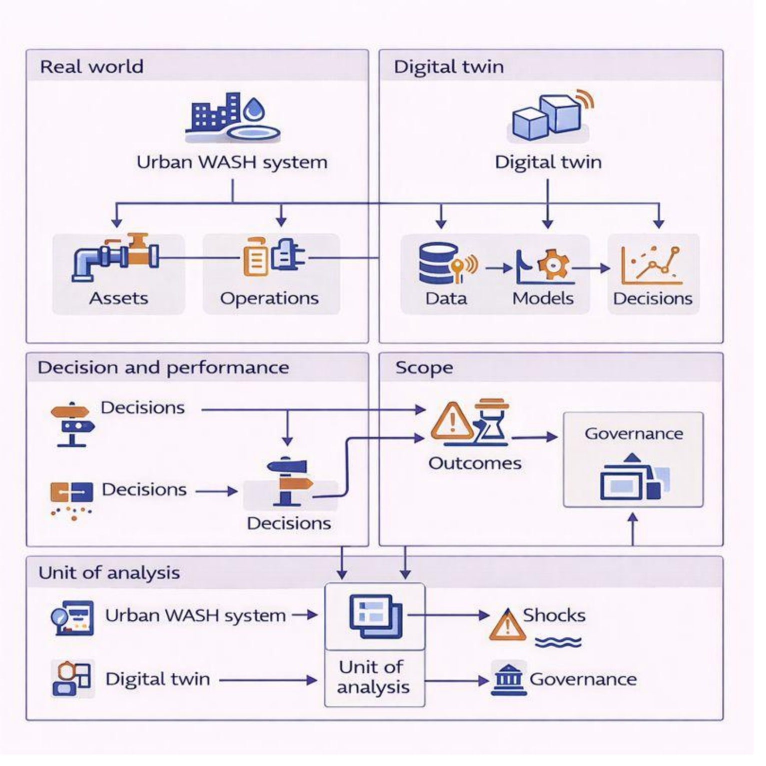

__Figure 4.__ Core constructs and definitions panel

Table 3. Key constructs and definitions

Construct	*Operational Definition*	*Unit/Scale*	*Coding Cue*
Pressure Prediction MAE	Mean abs pressure error	Meters	Group holdout MAE
Event Detection F1	F1 on burst/contam events	0-1	Stress scenario labels
Decision Support Uptime	DT available for decisions	Percent	SLO log uptime
Grouped Holdout	Split by entity/context	Split rule	No cross-ID leakage

BCa Bootstrap CI	Bias-corrected accel interval	95% CI	2000 resamples

Boundary Conditions and Applicability Across Geography and Service Level

Applicability across geography depends on the availability and stability of context signals, which can be uneven under crisis and across sensing infrastructures. Evidence from collective, near-real-time disaster sensing indicates that coverage and representativeness can shift with platform access and local communication practices (Moghadas et al., 2023). Table (4) summarizes boundary conditions and associated applicability limits for geographic transfer and service-level use. The framework therefore assumes public, city-level aggregates and becomes unsuitable when individual tracing or personally identifiable information is required.

Boundary conditions also govern evaluation and decision outputs. Grouped holdouts by geo-context groups are required to test transfer; independent and identically distributed cross-validation is not informative under spatial and institutional clustering. Preprocessing is restricted to training splits to prevent cross-split leakage, and an entity identifier audit is needed when common vendors or assets recur. Post-flood recovery analyses show that climate shocks and locally adjusted interventions condition outcomes, so stress tests should encode affordability and capacity bounds rather than assume unbounded resources (Li et al., 2022).

Table 4. Boundary conditions and applicability

Boundary	***Applies When***	***Fails When***	***Design Cue***
Public aggregate only	City-level indicators	Individual tracing needed	No PII policy
Grouped holdouts	Geo-context groups	IID CV only	Leave-group-out
Train-only preprocessing	Split isolation	Cross-split leakage	Entity ID audit
Constraint stress tests	Affordability, capacity	Unbounded resources	Encode hard bounds
Decision-only outputs	Policy guidance	Engineering drawings	No BoQ design

Mechanism Pathways From Sensors to Decisions to Resilience

Sensor-to-decision pathways in urban WASH digital twins are constrained by where sensing, inference, and optimization execute across edge and cloud nodes. Prior edge-cloud frameworks show that workload placement and offloading directly trade decision latency against bandwidth and energy, which matters under operational shocks (Lahza et al., 2024; Sathupadi et al., 2024; Shinde & Tarchi, 2024; Zhang et al., 2024). Scheduling policies further couple resource allocation to response time and success rates for digital-twin workloads (Lahza et al., 2024; Qi et al., 2024). Table (5) maps these mechanisms to operational cues, measurable implications, and validation handles.

Each pathway is paired with an observable indicator. For causal logic and mechanisms, governance-aware coding targets lower coding variance, supported by IRR and adjudication with Two annotators, 15%, while uncertainty reporting uses BCa bootstrap CI for decision thresholding with 2000 resamples. Equation (1) defines leakage-safe feature scaling by standardizing using training-split statistics, aligned with entity-ID audit expectations. Health staffing analogs clarify decision consequences under capacity limits (Băjenaru et al., 2024; Fischer et al., 2024), and structural pathway modeling can formalize these linkages (Fernandes et al., 2022).

$$s_i = \frac{x_i - \mu_{train}}{\sigma_{train}} \quad (1)$$

Table 5. Mechanisms and testable implications

Mechanism	*Operational Cue*	*Measurable Implication*	*Validation Handle*
Governance-aware coding	IRR and adjudication	Lower coding variance	Two annotators, 15%
Cohort realism bounds	Constraints and stress tests	Stable holdout metrics	Resource and climate
Leakage-safe learning	Train-only preprocessing	No split leakage	Entity-ID audit

Uncertainty reporting	BCa bootstrap CI	Decision thresholding	2000 resamples

Propositions and Implications

The propositions link urban context, data completeness, and governance constraints to digital-twin decisions for pressure management, event response, and continuity of service. Observable implications are specified in pressure prediction mae, event detection f1, and decision support uptime percent, with comparisons to an LSTM temporal model without physics, isolation forest anomaly detection, a static calibrated hydraulic model, and threshold-based alarm rules. A coding rubric is used to label constructs consistently so that propositions can be evaluated across utilities and asset managers.

The implications are bounded to programmatic cohorts built from public WASH statistics and operations proxies; site-specific engineering designs and clinical health trials are explicitly outside scope. Evaluation is intended to use grouped holdouts by entity and context, external holdouts by predefined groups, and train-only preprocessing with anchored tuning and an embargo to prevent lookahead. Robustness is appraised under concept drift over seasons, missing sensor slices, and shock scenarios for burst and contamination events.

H1 and H2: Grouped Holdouts and Primary Metrics Definitions

Grouped holdouts are used to test H1 and H2 under leave-group-out splits that separate evaluation groups by entity and context. Fig. (5) specifies the splits, metrics, and acceptance criteria required for auditable evaluation. Table (6) enumerates the split strategy, leakage control via entity ID separation with no cross-split leakage, and uncertainty reporting using BCa bootstrap confidence intervals with alpha 0.05. These pre-committed elements support research design transparency and evaluability by constraining tuning and interpretation to recorded rules across groups.

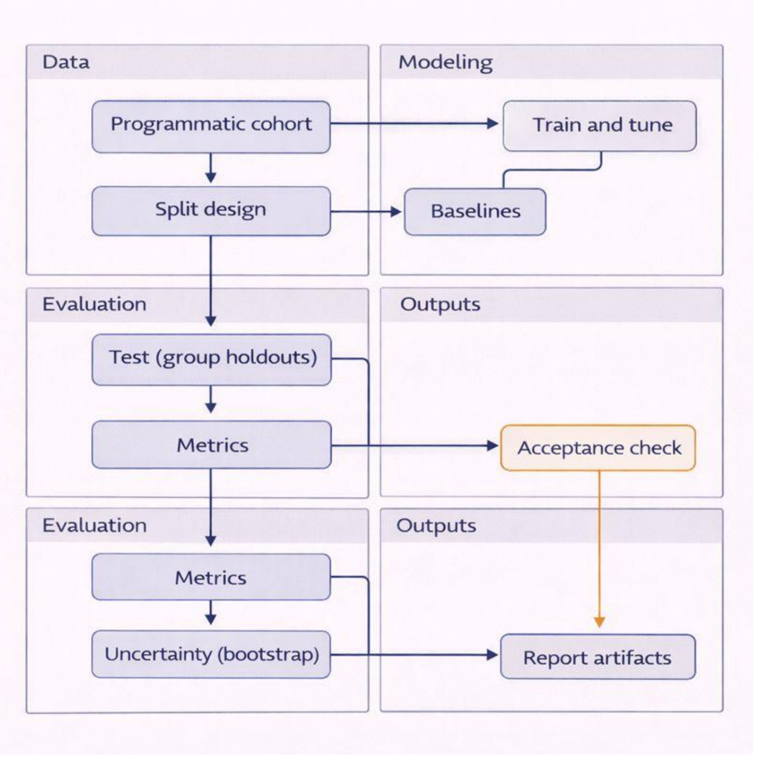

Figure 5. *Grouped holdout validation blueprint*

Mean Absolute Error (MAE) is the mean absolute difference between predicted and observed pressure over N samples, as defined in Equation (2). The F1 score summarizes event detection as the harmonic mean of precision and recall, as defined in Equation (3). Decision-support uptime percent is the fraction of available time over total time, expressed as a percent, as defined in Equation (4). Acceptance requires meeting AC1-AC3 on MAE, F1, and Uptime, with a halt rule when CI overlap with the baseline is >50%.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\hat{y}_i - y_i| \quad (2)$$

$$F1 = \frac{2\,Precision \cdot Recall}{Precision + Recall} \quad (3)$$

$$Uptime = 100 \cdot \frac{T_{available}}{T_{total}} \quad (4)$$

Table 6. Splits, metrics, and acceptance criteria

Element	*Specification*	*Acceptance*
Split Strategy	Grouped holdouts	Leave-group-out
Leakage Control	Entity ID separation	No cross-split leakage
Uncertainty Reporting	BCa bootstrap CI	Alpha 0.05
Primary Metrics	MAE, F1, Uptime	Meet AC1-AC3
Halt Rule	CI overlap baseline	Stop if >50%

Alternative Explanations: Static Hydraulic Model and Threshold Alarms

Static calibrated hydraulic models and threshold-based alarm rules provide plausible alternative explanations for decision-support gains in an urban WASH digital twin, because they can flag deviations without learning latent temporal structure. To operationalize these alternatives, hybrid edge-cloud baselines are considered in which lightweight anomaly detection runs at the edge and time-series prediction is centralized, consistent with resource-aware designs in predictive maintenance (Sathupadi et al., 2024). This framing enables direct contrasts against learning-based decision support while retaining realistic latency and bandwidth constraints.

The alternative explanations differ in mechanism: a static hydraulic model attributes pressure and flow residuals to fixed network parameters, whereas threshold alarms treat excursions as events independent of context. Learning-based pipelines, including edge anomaly detectors paired with cloud LSTM predictors (Sathupadi et al., 2024), can instead represent seasonality, demand shifts, and compound shocks, but risk confounding under incomplete sensing. Discrimination therefore requires evaluations under grouped holdouts, missing-sensor slices, and burst or contamination scenarios; empirical results for these contrasts are not reported here.

Robustness Stress Tests Under Monsoon Flood Risk and Resource Constraints

Monsoon-driven flooding can impose simultaneous shocks on urban WASH sensing, power availability, and connectivity, which constrains how a digital twin can update states and recommend actions. Sustainable AI work emphasizes that energy and compute budgets shape what can be deployed responsibly, not only what is accurate (León, 2024). For robustness of reasoning, stress tests are defined as counterfactual resource caps that force simplified inference, delayed updates, and selective monitoring, so resilience claims remain conditional on feasible operating budgets.

These constraints can reverse apparent advantages of data-hungry or frequently retrained components, especially when flood events co-occur with load shedding or limited on-premise capacity. Robustness of reasoning is strengthened by checking edge cases in which decision_support_uptime_percent is prioritized over marginal gains in pressure_prediction_mae or event_detection_f1, and by contrasting outcomes under static calibrated hydraulic model or threshold-based alarm rules. Quantitative energy accounting and hardware-specific profiling are not reported here, but should accompany deployment claims (León, 2024).

Limitations and Future Work

External validity remains the principal limitation because the proposed urban WASH digital twin framework is not accompanied by field results, and available analog evidence often relies on small monitored cohorts. Prior digital twin monitoring studies in healthcare report strong performance but use limited real-time participant counts and tightly controlled telemetry pipelines (Jameil & Al-Raweshidy, 2024, 2025). Fig. (6) summarizes failure modes, confounders, and misuse risks that can distort apparent gains. These limitations motivate cautious interpretation of any decision-support claims.

Future work should prioritize cohort-based validation with utilities and asset managers using grouped holdouts across contexts and geographies, and should report sensitivity to missing sensor slices and seasonal drift. Competing explanations, such as operational changes that coincide with model deployment, need explicit measurement to reduce confounding. Evidence from simulation-only urban optimization studies can overstate robustness when operational constraints and data fragmentation are absent (Lahza et al., 2024). Stronger falsification criteria and misuse guardrails are required before policy translation.

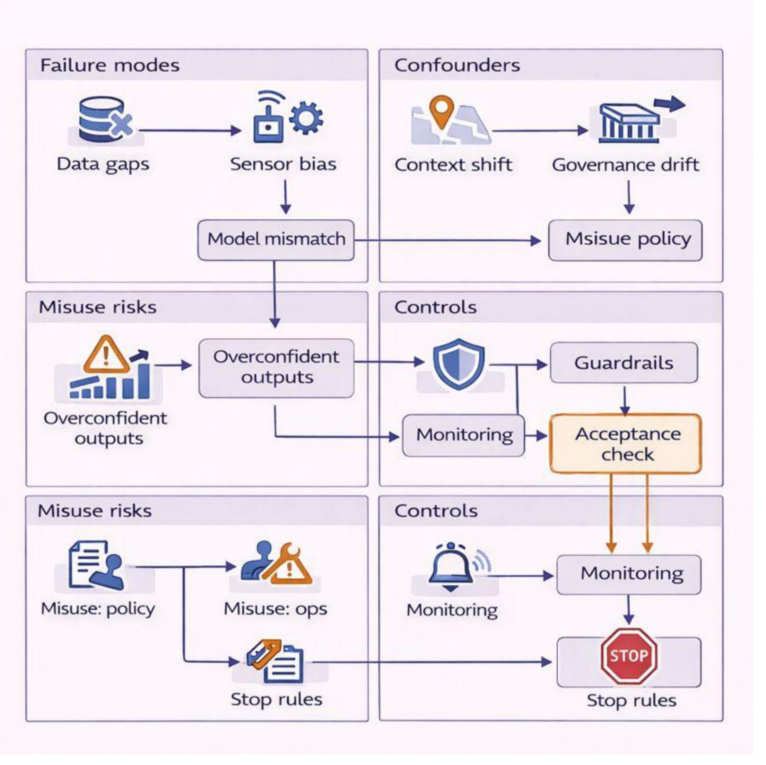

Figure 6. *Failure modes and misuse guardrails*

Conclusion

The present study specifies a decision-oriented conceptual model for urban WASH digital twins operating under incomplete and fragmented data. Context variables are mapped to performance and resilience decisions, and propositions are stated to make expected effects observable. A reviewer-facing coding rubric is defined to standardize construct labeling. A programmatic cohort validation design is outlined using grouped holdouts, train-only preprocessing, embargoed tuning, and BCa bootstrap confidence intervals against baseline models. Several constraints temper immediate claims. No empirical results are reported here, and the proposed Urban WASH DT Ops Cohort relies on public statistics and operational proxies that can omit local idiosyncrasies. Transfer across geographies is therefore treated as an explicit external-holdout question. Construct mis-coding remains a failure mode, motivating dual-annotator checks and adjudication. Decision support recommendations may be misapplied, so the framework is intended for policy guidance rather than site-specific engineering design.

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