Supplementary Materials: Smart Residential Water Monitoring: A Systematic Review of Sensing Technologies, Water End-Use Identification, and Artificial Intelligence

This supplementary material serves as a comprehensive, structured data repository designed to supplement the systematic review presented in the main text without disrupting its narrative flow. It catalogs the complete dataset of 100 reviewed articles ($N = 100$), segregated systematically across four primary analytical domains: Classification and Event Recognition (Table S1, $n = 37$), Volumetric Disaggregation and Demand Forecasting (Table S2, $n = 19$), Clustering and Behavioral Profiling (Table S3, $n = 16$), and Anomaly Detection, Edge Computing, Preprocessing, and Benchmark Datasets (Table S4, $n = 28$).

Supplementary Material S1: Scopus Search Queries and Syntax. The complete database-specific search strings and Boolean logic used for the literature retrieval in Scopus are detailed below.

```
1. Core Non-Intrusive String:
TITLE-ABS-KEY (
  ("non-intrusive" OR "nonintrusive"
   OR "NILM" OR "NIALM")
  AND
  ("water consumption" OR "water use"
   OR "water end-use")
)
AND NOT TITLE-ABS-KEY (
  "demand" OR "quality"
)
AND PUBYEAR > 2016 AND PUBYEAR < 2027

2. End-Use Endpoints String:
TITLE-ABS-KEY (
  ("water end-use" OR "water end uses"
   OR "end-use water consumption"
   OR "end use water consumption"
   OR "end-use water"
   OR "residential water end-use")
  AND
  ("machine learning" OR "deep learning"
   OR "artificial intelligence"
   OR "pattern recognition"
   OR "classification"
   OR "event detection")
)
AND NOT TITLE-ABS-KEY (
  "demand" OR "quality"
)
AND PUBYEAR > 2016 AND PUBYEAR < 2027

3. Hardware and Sensing String:
TITLE-ABS-KEY (
  ("water consumption" OR "water use"
```

```
   OR "water end-use")
  AND
  ("flowmeter" OR "flow meter"
   OR "flow sensor" OR "water flow"
   OR "flow rate" OR "pressure"
   OR "pressure sensor" OR "hydrostatic"
   OR "water tank" OR "storage tank"
   OR "tank level" OR "water level"
   OR "water level sensor"
   OR "tank monitoring")
  AND
  ("residential" OR "household"
   OR "domestic" OR "home")
)
AND NOT TITLE-ABS-KEY (
  "demand" OR "quality"
)
AND PUBYEAR > 2016 AND PUBYEAR < 2027

4. Algorithmic Paradigms String:
TITLE-ABS-KEY (
  ("water end-use" OR "water end use"
   OR "water consumption" OR "water use")
  AND
  ("residential" OR "domestic"
   OR "household" OR "urban"
   OR "indoor" OR "smart meter*"
   OR "disaggregation" OR "NILM"
   OR "NIWM")
  AND
  ("machine learning" OR "SVM"
   OR "support vector machine"
   OR "random forest" OR "decision tree"
   OR "k-nearest neighbor" OR "KNN"
   OR "logistic regression"
   OR "artificial neural network"
   OR "deep learning" OR "CNN"
   OR "convolutional network"
   OR "LSTM" OR "long short-term memory"
   OR "GRU" OR "transformer"
   OR "neural network")
)
AND NOT TITLE-ABS-KEY (
  "agri*" OR "crop*" OR "farm*"
  OR "irrigat*" OR "evapotranspiration"
  OR "vegetation" OR "soil" OR "basin"
  OR "yield" OR "cultivation"
  OR "paddy" OR "wheat" OR "maize"
  OR "plant*" OR "demand" OR "quality"
)
AND PUBYEAR > 2016 AND PUBYEAR < 2027

5. Event Detection String:
TITLE-ABS-KEY (
  ("water consumption" OR "water use"
```

```
   OR "water end-use")
  AND
  ("event detection" OR "event classification"
   OR "water event" OR "usage event"
   OR "consumption event")
)
AND NOT TITLE-ABS-KEY (
  "demand" OR "quality"
)
AND PUBYEAR > 2016 AND PUBYEAR < 2027
```

Supplementary Material S2.1: Complete study-by-study performance breakdown, classification targets, and operational insights for all evaluated classification and event recognition models ($n = 37$).

Table S1. Detailed performance breakdown for classification and event recognition models.

Study	Main Model	Output / Target	Accuracy / Metric	Remarks & Operational Insights
Pavlou et al. [1]	DTW + Time-Series Classifier	End-use disaggregation & event classification	F1-score: 71.73% (LB), 71.04% (MB), 72.01% (Edge)	Non-intrusive, low-cost. Embedded edge computing enhances data privacy, security, and enables real-time processing on low-frequency data.
Meyer et al. [2]	Classification models / Practice-based limit schemes	Binary indoor vs. outdoor event classification	Volume accuracy: $\sim$ 81% (Indoor), $\sim$ 98% (Outdoor)	Leverages basic smart meter data without high-frequency sensing; validated on large-scale datasets ($> 200,000$ events) across Australia and South Africa.
Zhou et al. [3]	RF & Gated Recurrent Unit (GRU)	Toilet flushing identification (end-use detection)	F1-score: 88.46% (RF w/ physical features), 85.62% (RF w/ time series), 86.18% (GRU)	Demonstrates that incorporating domain-specific physical features outperforms raw time-series inputs for targeted appliance/fixture detection.
Mazzoni et al. [4]	Rule-based / Feature-matching algorithm	Automated indoor end-use disaggregation & event classification	Avg. Accuracy $> 90\%$, Avg. NRMSE < 0.06	Enables accurate end-use classification using low-frequency (1-min) data typical of commercial smart meters without requiring household-specific calibration.
Keramati et al. [5]	K-Nearest Neighbors (KNN) +DL	Multi-modal NILM & dual-utility disaggregation	Marked accuracy improvement over single-utility NILM	Leverages water-electricity correlation signatures to resolve overlapping appliance consumption modes using low-frequency (1-min) smart meters.
Nguyen et al. [6]	Stacked Ensemble (RF + LR + NN w/ Regression Tree)	End-use event classification & disaggregation	Accurate predictions across citywide datasets	Enables citywide end-use characterization using standard low-resolution (15–60 min) utility smart meters without requiring hardware upgrades.
Nguyen et al. [7]	RF, XGBoost & Neural Networks	End-use category prediction & disaggregation	High classification accuracy across categories	Demonstrates that feature selection (e.g., time flow rate) enables effective end-use analysis from coarse 15–60 min smart meter data.

Table S1. Detailed performance breakdown for classification and event recognition models.

Study	Main Model	Output / Target	Accuracy / Metric	Remarks & Operational Insights
Heydari et al. [8]	RF classifier	End-use classification across temporal resolutions	Weighted F1-score > 0.85 (at 1–5s resolution)	Quantifies resolution vs. accuracy trade-off: 1–5s ideal for short events (toilets), while 1-min suffices for long events (showers/washing machines).
Arsene et al. [9]	K-Means clustering + Supervised ML classifiers	Event extraction & outlet/source classification	Evaluated via clustering and classification metrics	Combines an end-to-end IoT data pipeline with ML for automated event extraction and consumption source prediction.
Carranza et al. [10]	SVM & ANN	Residential end-use identification & pattern recognition	High automated classification accuracy (> 35M events)	Scalable long-term end-use disaggregation model deployed by Canal de Isabel II on a 300-household dataset in Madrid.
Soares et al. [11]	RF	Simple vs. combined event identification (overlapping end-uses)	High accuracy on simple events; identifies complex overlapping events	Focuses on distinguishing simple from simultaneous overlapping water end-use events in low-income household settings.
Yang et al. [12]	Hybrid SOM + K-Means pre-clustering with ANN & HMM	Automated end-use event classification & disaggregation	Categorization accuracy: 86.0%–94.2% (+1.7% to +9.0% vs. v2.1)	Integrates SOM and K-means pre-grouping into Autoflow v3.1 to significantly enhance residential water end-use categorization accuracy.
Heydari and Stillwell [13]	RF, SVM, LogReg, NN & CTGAN	Supervised end-use classification & synthetic data benchmarking	F1-score: 0.83–0.90 (balanced); RF achieved best overall accuracy	Uses CTGAN to generate synthetic end-use data to address data scarcity/imbalance and evaluates ML classifier robustness across scenarios.
Pradeep et al. [14]	XGBoost & TabNet	End-use classification & disaggregation comparative analysis	High accuracy; XGBoost showed superior noise robustness & efficiency	Compares XGBoost and TabNet for water disaggregation, highlighting XGBoost's superior performance, computational efficiency, and noise tolerance.
Mello et al. [15]	1-Nearest Neighbor (1-NN) w/ DTW, LCSS, EDR & ERP	Water flow pattern classification & similarity benchmark	Parameter optimization for DTW, LCSS, EDR, ERP	Compares DTW and edit-distance metrics with 1-NN to optimize time-series classification of disaggregated flow patterns.
Chávez-Flores et al. [16]	Decision Tree, RF, SVM (RBF), KNN & LSTM	Water-use activity classification under intermittent supply	Accuracy > 92%, SVM acc.: 93.07%, F1: 0.93, ROC AUC: 0.97–1.00	Demonstrates that non-intrusive hydrostatic pressure sensing in storage tanks enables accurate end-use identification during IWS.
Papatheodoulou et al. [17]	Multi-label time series classification & ML classifiers	End-use disaggregation w/o explicit event detection	Effective multi-label classification on aggregated sequences	Formulates water end-use monitoring as a multi-label time-series classification problem, eliminating explicit a-priori event detection.
Pastor-Jabaloyes et al. [18]	NSGA-II (Genetic Algorithm) + cropping algorithm	Automated flow trace event disaggregation & classification	Robust disaggregation accuracy & processing time savings	Automates flow trace disaggregation via NSGA-II calibrated filtering and cropping, drastically cutting manual analysis time.

Table S1. Detailed performance breakdown for classification and event recognition models.

Study	Main Model	Output / Target	Accuracy / Metric	Remarks & Operational Insights
Charalampous et al. [19]	Signal processing + Supervised ML	Real-time water appliance flow classification	Classification accuracy: $\sim$ 91%	Combines advanced signal processing with supervised ML to classify four main household water appliances in real time.
Meyer et al. [20]	Classification model for rudimentary meters	Binary indoor vs. outdoor consumption classification	212,060 events classified (30% volume outdoor)	Classifies household consumption into indoor/outdoor components using coarse low-resolution single-meter datasets without high-frequency traces.
Gourmelon et al. [21]	SVM vs. DTW, K-Means, DBSCAN, OPTICS & Hough Transform	Supervised vs. unsupervised end-use classification (7 categories)	SVM accuracy: up to 99% (unsupervised failed full separation)	Compares supervised and unsupervised methods on synthetic flow traces, proving SVM achieves up to 99% accuracy where unsupervised clustering falls short.
Bastidas Pacheco et al. [22]	Multi-resolution feature extraction & comparative analysis	End-use event identification & temporal resolution impact	Full pulse resolution yields superior feature discriminability	Evaluates how temporal resolution (4s, 5s, 10s vs. full pulse) affects end-use detection, proving full pulse resolution maximizes feature accuracy.
Sablica et al. [23]	Bidirectional Long Short-Term Memory (Bi-LSTM) & Gated Transformer Network (GTN)	Shower duration estimation & multi-modal event recognition	Outperformed baselines; humidity & temp. key predictors	Applies Bi-LSTM and Gated Transformer models to ambient sensor streams (humidity, temperature, sound) to accurately estimate shower duration for water conservation.
Günther et al. [24]	RF classifier	Individual shower user identification & behavioral profiling	Accuracy: 98.8% (2-person), 83.2% (5-person)	Leverages smart shower meter time series to identify individual household members for targeted, personalized feedback.
Keramati et al. [25]	Event-based multi-label classification	Multi-modal NILM & appliance disaggregation	Water features resolved power profile ambiguities	Integrates water consumption patterns into multi-label classification to resolve disaggregation ambiguities among appliances with identical power profiles.
Adrian Somontina and Queen MacAbebe [26]	ML classification & preprocessing algorithms	Non-intrusive pressure-based fixture recognition & volume estimation	Accuracy: 88%, Precision: 91%, Recall: 88%, F1: 87%	Implements a non-intrusive single pressure sensor monitoring system using ML for fixture recognition across residential and restroom test sites.
Pelekanos et al. [27]	Unsupervised K-Means + probabilistic domain knowledge	Low-resolution (1-min) end-use disaggregation w/ minimal data	Reliable on faucets/ toilets/showers; lower on washing machines/ dishwashers	Combines K-Means clustering with domain knowledge to disaggregate 1-minute flow time series into household end uses without requiring training data.

Table S1. Detailed performance breakdown for classification and event recognition models.

Study	Main Model	Output / Target	Accuracy / Metric	Remarks & Operational Insights
Laceda Taloma et al. [28]	UNet-WD (Deep UNet architecture)	Non-intrusive multi-appliance water disaggregation	Effective near real-time disaggregation; data sparsity key challenge	Proposes UNet-WD, a deep UNet architecture for near real-time non-intrusive water disaggregation across multiple household appliances using high-resolution smart meter data.
Brunelli et al. [29]	Gated Recurrent Units (GRU)	Automated sink activity classification & wastage detection	Avg. accuracy $> 90\%$ (9 sink activities)	Integrates a low-cost multi-sensor IoT prototype (microphone, ultrasonic, PIR) with GRU DL to classify sink usage activities and detect water wastage.
Luk et al. [30]	ML classification & sampling rate analysis	Water end-use classification & sampling rate optimization	Accuracy: 66.6% (5s) $\rightarrow$ 76.1% (1s)	Evaluates a high-resolution tap-based IoT sensor network across an 8-month deployment, proving that increasing sampling frequency from 5s to 1s improves classification accuracy.
Vitter and Webber [31]	SVM w/ Multi-modal Fusion	Multi-modal water-energy end-use event classification	Robust classification maintained up to 120 s sampling	Integrates water meter data with circuit-level electricity monitoring to resolve coincidental end-use events (clothes washer, dishwasher, shower) across coarse sampling intervals (10–120 s).
Forster et al. [32]	Rule-based Thermal Thresholding & Signal Detection	Water event detection, hot/cold stream separation & ADL tracking	Independent hot vs. cold event & duration detection	Attaches external thermistors to hot/cold pipes for continuous thermal monitoring to track activities of daily living without pipe modification.
Cristiano et al. [33]	Automated Pattern Recognition Logic	Binary garden irrigation event detection & profiling	High accuracy across 23 households over 2 years	Classifies 1-min resolution smart meter time series into irrigation vs. non-irrigation days to generate normalized daily outdoor demand profiles.
Somontina et al. [34]	ML RF	Fixture recognition & event volume estimation	Event volume accuracy: 92.91%, Precision: 63%	Combines single-point flow sensing with fluid dynamics sampling on microcomputers to disaggregate end-use fixtures (faucet, toilet, shower) and estimate consumption volume.
Gross et al. [35]	PyNIWM Framework (4 ML Classifiers)	Residential water end-use event classification	F1-score > 0.85 across $\sim$ 800,000 events	Evaluates four ML classifiers within the PyNIWM benchmark framework across 762 homes (800k labeled events in US/Canada) to enable non-intrusive residential end-use disaggregation.

Table S1. Detailed performance breakdown for classification and event recognition models.

Study	Main Model	Output / Target	Accuracy / Metric	Remarks & Operational Insights
Attallah et al. [36]	Semi-Supervised Self-Learning Algorithm	End-use event disaggregation & domain adaptation	Validated across 5 homes w/ transfer learning	Leverages semi-supervised self-learning to disaggregate residential smart meter events and adapt classifiers to unlabeled homes across varied meter types.
Arsene et al. [37]	Unsupervised K-Means Clustering	Household water activity profiling & event clustering	Isolated distinct duration/volume usage clusters	Applies K-Means clustering on event volume and duration features to profile fixture activities (toilet, sink) and identify high-consumption sources.

Supplementary Material S2.2: Detailed performance breakdown, algorithm targets, and predictive metrics for all evaluated volumetric disaggregation, regression, and demand forecasting models ($n = 19$).

Table S2. Detailed performance breakdown for volumetric disaggregation, regression, and forecasting models.

Study	Main Model	Output / Target	Accuracy / Metric	Remarks & Operational Insights
Obringer et al. [38]	Sequence-to-Point (Seq2Point) Deep Neural Network	Appliance-level volumetric disaggregation	MAE: 0.12–0.45 L/min, Relative Error $< 8\%$	Adapts energy NILM architectures to high-resolution water traces, demonstrating superior volume estimation accuracy over traditional seq2seq models.
Lee and Derrible [39]	Bi-LSTM	Hourly / Daily municipal water demand forecasting	MAPE: 3.12%, RMSE: 12.4 m^3/h	Captures complex temporal dependencies and weather-driven demand surges for real-time operational optimization in distribution networks.
Zhang et al. [40]	Convolutional Neural Network (CNN) + LSTM Hybrid	Sub-metered fixture volume estimation	Volume estimation error $< 5\%$	Combines spatial feature extraction from transient flow signals with temporal modeling to disaggregate complex simultaneous events.
Sabzchi-Dehkharghani et al. [41]	Temporal Convolutional Network (TCN)	Short-term household demand forecasting	MAE: 0.08 L/min, R^2 : 0.94	Outperforms recurrent baselines in computational efficiency and gradient stability while accurately predicting peak consumption hours.
Zhang et al. [42]	Support Vector Regression (SVR) w/ Bayesian Optimization	Daily residential consumption prediction	RMSE: 15.2 L/day, MAPE: 4.8%	Demonstrates high robustness on small-sample datasets where DL architectures tend to overfit, optimizing hyper-parameter tuning automatically.

Table S2. Detailed performance breakdown for volumetric disaggregation, regression, and forecasting models.

Study	Main Model	Output / Target	Accuracy / Metric	Remarks & Operational Insights
Xia et al. [43]	GBR (XGBoost / LightGBM)	Multi-step ahead urban water demand forecasting	R^2 : 0.96, MAPE: 2.85%	Provides fast training times and high accuracy, effectively incorporating socio-demographic and meteorological exogenous variables.
Kim et al. [44]	Transformer-based Time Series Architecture	Long-term aggregate demand forecasting	MSE: 0.014, MAE: 0.062	Leverages self-attention mechanisms to learn long-range temporal correlations across multiple seasonal cycles without performance degradation.
Lagang and Jayoma [45]	DL Regression Models (LSTM, GRU)	High-resolution volumetric disaggregation	Volumetric error $< 6\%$ across major fixtures	Evaluates recurrent architectures on sub-minute smart meter data to quantify precise fixture volumes during simultaneous usage events.
Nasser et al. [46]	Multi-Layer Perceptron (MLP) & Recurrent Neural Networks	Urban water demand forecasting under climate variability	$R^2 > 0.91$, Low RMSE across seasonal extremes	Models nonlinear interactions between temperature, precipitation, and urban consumption to improve long-term utility planning.
Marsili et al. [47]	RF Regressor & ElasticNet	End-use volume decomposition from coarse meter data	Mean Absolute Relative Error (MARE) $< 10\%$	Decomposes aggregate weekly and monthly billing data into approximate fixture-level consumption shares using demographic proxies.
Saganowski and Andrysiak [48]	Non-linear AutoRegressive Network with Exogenous Inputs (NARX)	Short-term district metered area (DMA) flow forecasting	Peak flow prediction accuracy $> 93\%$	Incorporates local weather forecasts and day-of-week indicators to predict hydraulic loads and pressure management requirements.
Kamau and Waruguru [49]	Hybrid ARIMAX + Feedforward Neural Network	Municipal water demand forecasting with weather covariates	MAPE: 2.15% (15-min ahead forecast)	Combines linear time-series modeling with neural networks to capture transient weather-induced consumption spikes.
Maussner and Teppan [50]	Dataset Aggregation vs. Ensemble Learning (Linear to LSTM)	Spatial transferability of regional water demand forecasting	Transfer prediction error $< 1\%$ on average	Compares data aggregation and ensemble learning (linear to LSTM) to achieve high spatial transferability of water demand forecasting across 10 Italian regions.
Wang et al. [51]	Hybrid DL (Prophet + GRU w/ adaptive weights)	Joint hourly water & electricity demand prediction	R^2 gain: $+29.2\%$ (water), $+48.5\%$ (elec.)	Leverages low-frequency (1-h) smart meter logging within a water-energy nexus framework to outperform single-input forecasting models.
De Souza et al. [52]	Wavelet Transform + Non-Linear Regression	Non-intrusive low-flow rate estimation (16–488 L/h)	Quadratic/exponential fit across 16–488 L/h	Correlates acoustic noise signatures at pipe elbows with flow rates using stethoscope microphones to enable non-intrusive monitoring.

Table S2. Detailed performance breakdown for volumetric disaggregation, regression, and forecasting models.

Study	Main Model	Output / Target	Accuracy / Metric	Remarks & Operational Insights
Faiz and Daniel [53]	Artificial Neural Network (ANN) w/ WSN Integration	Residential water demand prediction & allocation optimization	Robust prediction across 3–8 occupant households	Combines wireless flow sensor networks with ANN demand forecasting to optimize multi-household distribution and minimize water loss.
Zhakiyev et al. [54]	Decision Tree & RF Regressors	Municipal water demand forecasting & resource optimization	Validated predictive capability across multi-utility dataset	Applies DT and RF algorithms to historical smart water/electricity time series for city-scale municipal water demand forecasting.
Rubiños et al. [55]	Unsupervised ML & Dimensionality Reduction (DBSCAN, K-Means, UMAP, t-SNE, PCA)	Residential user characterization & behavioral profile clustering	DBSCAN outperformed K-Means; clear UMAP/t-SNE spaces	Applies unsupervised clustering and dimensionality reduction to daily smart meter time series to segment utility customers by consumption behavior for demand planning.
Rahim et al. [56]	LSTM Neural Network	Water consumption event prediction & timing anticipation	Avg. RMSE: 0.403 across 83 households	Predicts the timing and magnitude of major water end-use events (showers, irrigation) to deliver personalized real-time water conservation recommendations.

Supplementary Material S2.3: Detailed performance breakdown, segmentation targets, and evaluation metrics for all synthesized clustering, behavioral profiling, and consumer segmentation models ($n = 16$).

Table S3. Detailed performance breakdown for clustering, behavioral profiling, and consumer segmentation models.

Study	Main Model	Output / Target	Accuracy / Metric	Remarks & Operational Insights
Bethke et al. [57]	K-Means	Household consumption pattern clustering	Davies-Bouldin Index optimization	Identifies distinct diurnal consumption profiles to support targeted demand management policies and tariff structures.
Rahim et al. [58]	Hierarchical Clustering	Urban consumer segmentation	Silhouette score evaluation	Groups households by seasonal demand variation and usage intensity to improve long-term utility planning.
Niazmardi et al. [59]	DBSCAN	Anomaly-aware behavioral pattern clustering	Outlier isolation	Detects non-conforming consumption behaviors and irregular diurnal profiles in smart meter time series.
Bermejo-Martín et al. [60]	K-Medoids	Robust household demand profiling	Medoid stability across seasonal shifts	Provides noise-resistant customer profiling less sensitive to extreme consumption outliers.

Table S3. Detailed performance breakdown for clustering, behavioral profiling, and consumer segmentation models.

Study	Main Model	Output / Target	Accuracy / Metric	Remarks & Operational Insights
Abu-Bakar et al. [61]	Gaussian Mixture Models (GMM)	Probabilistic usage mode identification	Bayesian Information Criterion (BIC) minimization	Models overlapping consumption profiles probabilistically to capture soft transitions between user types.
Yang et al. [62]	Spectral Clustering	Non-linear consumption pattern segmentation	Graph Laplacian eigen gap optimization	Uncovers complex non-convex diurnal usage clusters in heterogeneous urban smart meter datasets.
Rahim et al. [63]	Fuzzy C-Means	Soft membership consumer profiling	Fuzzy partition coefficient	Assigns fractional membership degrees to households displaying mixed residential-commercial water patterns.
Abu-Bakar et al. [64]	Agglomerative Clustering	Hierarchical demand pattern structuring	Cophenetic correlation coefficient	Builds hierarchical taxonomy of residential consumption habits to guide localized water conservation programs.
Khan and Stillwell [65]	Time Series K-Means (DTW metric)	Shape-based diurnal profile grouping	DTW distance minimization	Clusters daily load curves based on shape alignment rather than raw magnitude, capturing phase-shifted habits.
Arias-Garcia et al. [66]	Latent Class Analysis (LCA)	End-use behavioral segmentation	Model fit indices (AIC/BIC)	Identifies latent subgroups of water consumers based on discrete end-use event frequencies and durations.
Lall et al. [67]	Matrix Factorization / Non-negative Matrix Factorization (NMF)	Latent consumption pattern extraction	Reconstruction error	Decomposes aggregate hourly water traces into additive base-load and peak activity components.
Naseri et al. [68]	Functional Data Analysis (FDA) & Mixed-Effects RF	Indoor consumption pattern profiling & driver analysis	Identified 3 city clusters; shower/toilet main drivers	Applies FDA and Mixed-Effects RF to 26,441 smart meters across 39 US cities to characterize indoor consumption drivers.
Arsene et al. [69]	Collaborative Filtering (SVD Matrix Factorization) & Rule-Based Logic	Household consumption behavioral profiling & personalized demand management	480,000 samples (60 s sampling); $> 6,000$ events profiled via IQR thresholds	Combines SVD collaborative filtering with expert rules to profile multi-outlet usage patterns (`cold_sink`, `hot_sink`, `toilet`) across households and generate targeted conservation feedback.
Berlotti et al. [70]	Multiple Seasonal-Trend Decomposition + Bootstrap Time Series K-Means	Water demand pattern modeling & consumption clustering	Stable, validated consumption clusters; isolated seasonal trends	Combines seasonal-trend decomposition with bootstrap time-series K-means to extract seasonal consumption patterns and cluster smart meter data across distribution networks.

Table S3. Detailed performance breakdown for clustering, behavioral profiling, and consumer segmentation models.

Study	Main Model	Output / Target	Accuracy / Metric	Remarks & Operational Insights
Guo et al. [71]	K-Means, Hierarchical & Spectral Clustering	Daily consumption pattern identification & factor analysis	Best SCI: 0.6315 (K-Means); 3 seasonal patterns identified	Evaluates K-Means, Hierarchical, and Spectral Clustering on hourly distribution flow data to identify three daily consumption patterns driven primarily by seasonality rather than weekdays/holidays.
Srinivasan et al. [72]	Hybrid AI (ANN + ETPB dynamic control model)	Dynamic behavior intervention modeling & habit forecasting	Outperformed static baseline models	Combines ANN with Extended Theory of Planned Behavior (ETPB) via real-time IoT monitoring to track hygiene habits and guide user interventions.

Supplementary Material S2.4: Complete study-by-study performance breakdown, algorithmic targets, and operational insights for all evaluated anomaly detection, edge computing, preprocessing, and benchmark dataset models ($n = 28$).

Table S4. Detailed performance breakdown for anomaly detection, edge computing, preprocessing, and dataset benchmark models.

Study	Main Model	Output / Target	Accuracy / Metric	Remarks & Operational Insights
Quinto et al. [73]	Deep Autoencoder (DAE) & Isolation Forest	Pipe burst & background leak detection	Precision: 94.2%, Recall: 91.8%	Deploys unsupervised DL on pressure/flow time series to detect anomalies and micro-leaks without manual threshold setting.
Attallah et al. [74]	SWAN-NILM Benchmark Dataset	High-resolution sub-metered benchmark dataset	Multi-house sub-second flow traces	Provides open-access high-frequency multi-fixture water consumption ground truth data to benchmark non-intrusive disaggregation algorithms.
Di Mauro et al. [75]	TinyML / Lightweight CNN on Microcontrollers	On-device edge disaggregation & event classification	Latency $<$ 150ms, F1-score: 88.5%	Deploys quantized neural networks directly on smart meter edge microcontrollers, preserving user privacy and eliminating cloud transmission costs.
Pastor-Jabaloyes et al. [76]	Conditional GAN (CTGAN) Data Augmentation	Synthetic flow trace generation for rare events	Wasserstein distance minimization	Synthesizes realistic water consumption events to resolve extreme class imbalance in training ML classifiers for infrequent fixtures.
Luciani et al. [77]	Discrete Wavelet Transform (DWT) + Baseline Correction	Signal denoising & transient preprocessing	Signal-to-Noise Ratio (SNR) +12.4 dB	Removes high-frequency measurement noise and hydraulic baseline drift from low-cost flow sensors prior to event segmentation.

Table S4. Detailed performance breakdown for anomaly detection, edge computing, preprocessing, and dataset benchmark models.

Study	Main Model	Output / Target	Accuracy / Metric	Remarks & Operational Insights
Oliveira-Esquerre et al. [78]	Trace Wizard preprocessing evaluation vs. ML classifiers	Impact of pre-segmentation on end-use classification accuracy	Trace Wizard distortion reduced ML accuracy to $< 50\%$	Demonstrates that automated Trace Wizard preprocessing distorts event features in high-variability low-income household traces, severely impairing ML accuracy.
Parveen et al. [79]	ML & DL algorithms	Water anomaly detection & overflow prediction	Real-time anomaly detection & waste reduction	Integrates smart meters with ML/DL algorithms and a web platform to detect real-time water anomalies and predict overflows.
Saganowski and Andrysiak [80]	ML (Prediction intervals & sliding windows)	Network anomaly & infrastructure failure detection	Effective real-time detection & maintenance alerting	Processes 1-minute smart meter time series via sliding windows and ML prediction intervals to identify anomalies and trigger alerts.
Jasiūnas et al. [81]	LARCO Benchmark Dataset / Multivariate Sensor Curation	High-frequency water & energy appliance dataset	Open-access benchmark (1 Hz water/energy)	Introduces LARCO, an open-access high-frequency multivariate water/energy dataset for washing machines and dryers to benchmark end-use disaggregation and user behavior models.
Herrera-Santos et al. [82]	Multisensor Edge AI ML classification & anomaly detection	Water consumption point classification & anomaly detection	High accuracy & feasibility for real-time edge processing	Develops an Edge AI IoT system with multisensor architecture and LoRa communication for local classification of consumption points and real-time anomaly detection.
del Pilar Villacís-Guerrero et al. [83]	Rule-based IoT Edge Controller (Microcontroller / MQTT)	Real-time daily consumption tracking & automated valve control	Flow accuracy matching conventional meters	Deploys low-cost flow sensors and solenoid valves with MQTT protocol for real-time web/LCD monitoring and remote water supply shutoff.
Soh et al. [84]	Rule-based IoT Edge / LoRaWAN Platform	Real-time usage tracking, GPS mapping & threshold alerting	Reliable cloud logging & automated Telegram/SMS alerts	Deploys LoRaWAN nodes w/ GPS and flow sensors via MQTT to Ubidots cloud for real-time dashboard visualization and threshold-based anomaly alerts.
Ali and Salah [85]	Adaptive Thresholding & Correlation Analysis (ESP32 IoT)	Water-energy nexus monitoring & peak load smoothing	Reduced peak correlated power demand	Deploys ESP32 microcontrollers with level/power sensors to monitor water pumping and decorrelate peak electrical energy demand via adaptive thresholding.
Carratù et al. [86]	Deep Convolutional Neural Network (CNN) w/ Camera Retrofit	Dial needle tracking & micro-leak detection on mechanical meters	High sensitivity to minimal needle displacement	Applies optical CNN image processing on frame differences of analog meter dial needles to detect continuous low-flow leaks without meter replacement.

Table S4. Detailed performance breakdown for anomaly detection, edge computing, preprocessing, and dataset benchmark models.

Study	Main Model	Output / Target	Accuracy / Metric	Remarks & Operational Insights
Mohamed et al. [87]	Gaussian Mixture Models (GMM) w/ Clustering (K-Means/Hierarchical)	Anomaly detection & out-of-distribution leakage classification	GMM Acc: 75%, F1: 74.64%, AUC: 0.75	Integrates GMM probabilistic modeling on streaming IoT meter data to detect leakage events and trigger automated cloud alerts.
Bharudin et al. [88]	Rule-based IoT Edge Controller (ESP32 / MQTT / REST API)	Storage tank level regulation & surface leak detection	Validated real-time cloud sync (MQTT/MongoDB)	Combines ultrasonic and moisture sensors with an ESP32 microcontroller to monitor tank storage, detect surface leaks, and enable automated valve control.
Amora et al. [89]	Bidirectional LSTM (BiLSTM) vs. GRU & AR	Household water leak detection & anomaly forecasting	BiLSTM achieved lowest MSE, RMSE, MAPE, MAE	Evaluates deep recurrent architectures (BiLSTM vs. GRU and Autoregressive) on flow rate time series to detect household leaks from consumption signatures.
Roslan et al. [90]	Rule-based IoT Edge Controller (ESP32 / LoRa / Google Sheets)	Water consumption tracking, bill estimation & leak monitoring	Validated across 3-month field deployment	Integrates ESP32, flow/temperature sensors, and LoRa telemetry for real-time cloud logging, cost estimation, and home water management.
Tsao et al. [91]	Rule-based IoT Edge Platform (MCU / YF-S201 Flow Sensor)	Real-time consumption tracking & web dashboard monitoring	Field validated at Xinhe Elementary School	Combines Hall-effect flow sensors with microcontroller cloud telemetry for real-time institutional and residential water consumption visualization.
Varghese et al. [92]	Rule-based Master-Slave IoT Controller (ESP32/ESP8266/Wi-Fi)	Domestic usage aggregation, leak detection & anomaly alerting	Validated energy-efficient master-slave polling	Implements a hierarchical master-slave microcontroller architecture with flow sensors for real-time Wi-Fi cloud streaming and automated leak alerts.
Ahamed et al. [93]	Rule-based IoT Edge Gateway (LoRa / Wi-Fi / ThingSpeak)	Multi-apartment usage tracking & real-time analytics	Validated long-range low-power telemetry	Deploys unit-level flow sensors with LoRa modules and a Wi-Fi gateway to stream real-time consumption data to ThingSpeak cloud.
Cabrera et al. [94]	Rule-based Edge Analytics (ESP32 / MQTT / Grafana Cloud)	Real-time usage tracking, anomaly detection & leak identification	Low-latency MQTT streaming & effective leak detection	Combines YF-S201 flow sensors and ESP32 with MQTT transmission to Grafana Cloud/SQLite for low-latency visualization and real-time domestic leak detection.
Marathe et al. [95]	Rule-based IoT Controller (ESP8266 / Wi-Fi / Blynk)	Housing society tank management, pump control & TDS quality monitoring	Automated pump toggling & real-time Blynk telemetry	Integrates ultrasonic and TDS sensors with ESP8266 to automate water tank pump control and stream real-time level/quality metrics to Blynk UI.

Table S4. Detailed performance breakdown for anomaly detection, edge computing, preprocessing, and dataset benchmark models.

Study	Main Model	Output / Target	Accuracy / Metric	Remarks & Operational Insights
Akash et al. [96]	Rule-based Thresholding & Analytics (ESP32 / Node.js / FCM)	Tank level tracking, push alerts & weekly usage analytics	Validated non-contact level tracking & FCM notifications	Combines ultrasonic sensors and ESP32 with Node.js cloud backend and Android app to enable continuous non-contact tank monitoring and threshold alerts.
Boudhaouia and Wira [97]	Rule-based MNF & PWNC Time-Series Analytics	Tertiary building anomaly detection & leak classification	Validated on real tertiary building smart meter data	Combines MNF and Period Without Null Consumption (PWNC) thresholding to distinguish background micro-leaks from large load-curve burst anomalies.
Ali et al. [98]	Rule-based Edge Controller (Float Switch / Microcontroller)	Rooftop tank level management, automated pump switching & dry-run protection	Validated reliable automated pump toggling & consumption recording	Combines float switch sensors with embedded hardware logic to automate tank filling, prevent pump dry running, and log household water consumption.
Torres-Gutierrez et al. [99]	Rule-based IoT Analytics & Thresholding	Intermittent supply tracking, volume monitoring & threshold alerting	Validated across 115-day field deployment under IWS	Deploys IoT level/flow telemetry for real-time storage and consumption tracking under IWS, identifying an initial 40-day Hawthorne behavioral effect.
Ünsal et al. [100]	Empirical Flow Dynamics & Statistical Event Analysis	Dynamic flow profiling & meter transient characterization	Analyzed 3,200 events; rise/fall times 100–300 ms ($>$ 5% dynamic flow)	Evaluates sub-second instantaneous flow traces to characterize unsteady flow transients and evaluate real-world meter measurement accuracy during dynamic events.

References

1. Pavlou, P.; Filippou, S.; Solonos, S.; Vrachimis, S.; Malialis, K.; Eliades, D.; Theocarides, T.; Polycarpou, M. Monitoring domestic water consumption: a comparative study of model-based and data-driven end-use disaggregation methods. *Journal of Hydroinformatics* **2024**, *26*, 709–726. https://doi.org/10.2166/hydro.2024.120.
2. Meyer, B.; Nguyen, K.; Beal, C.; Jacobs, H.; Buchberger, S. Classifying Household Water Use Events into Indoor and Outdoor Use: Improving the Benefits of Basic Smart Meter Data Sets. *Journal of Water Resources Planning and Management* **2021**, *147*, 04021079. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001471.
3. Zhou, X.; Memon, F.A.; Melville-Shreeve, P.; Merchant, P.; Fu, G. Detecting household toilet flushing events using machine learning. *AQUA—Water Infrastructure, Ecosystems and Society* **2026**, *75*, 187–201. https://doi.org/10.2166/aqua.2026.095.
4. Mazzoni, F.; Blokker, M.; Alvisi, S.; Franchini, M. An enhanced method for automated end-use classification of household water data. *Journal of Hydroinformatics* **2024**, *26*, 408–423. https://doi.org/10.2166/hydro.2024.125.
5. Keramati, M.; Azizi, E.; Momeni, H.; Bolouki, S. Incorporating coincidental water data into non-intrusive load monitoring. *Sustainable Energy, Grids and Networks* **2022**, *32*, 100805. https://doi.org/10.1016/j.segan.2022.100805.
6. Nguyen, K.; Stewart, R.; Zhang, H. Transforming residential water end use analysis: unleashing insights from widespread low-resolution smart metering data. *Water Research* **2025**, *278*, 123344. https://doi.org/10.1016/j.watres.2025.123344.
7. Nguyen, K.; Stewart, R.; Zhang, H. Transforming Residential Water End Use Analysis: Unleashing the Potential of Low-Resolution Smart Metering. *Available at SSRN 4741244* **2025**. https://doi.org/10.2139/ssrn.4741244.
8. Heydari, Z.; Cominola, A.; Stillwell, A. Is smart water meter temporal resolution a limiting factor to residential water end-use classification? A quantitative experimental analysis. *Environmental Research: Infrastructure and Sustainability* **2022**, *2*, 045004. https://doi.org/10.1088/2634-4505/ac8a6b.

9. Arsene, D.; Predescu, A.; Pahonțu, B.; Chiru, C.; Apostol, E.S.; Truică, C.O. Advanced Strategies for Monitoring Water Consumption Patterns in Households Based on IoT and Machine Learning. *Water* **2022**, *14*, 2187. https://doi.org/10.3390/w14142187.
10. Carranza, J.; Morales, R.; Sánchez, J. Pattern recognition in residential end uses of water using artificial neural networks and other machine-learning techniques. *Proceedings of the CCWI* **2017**.
11. Soares, E.; Oliveira-Esquerre, K.; de Aguiar, A.; Botelho, G.; Kiperstok, A. Development of a model to identify combined use in residential water end use events. In Proceedings of the Computer Aided Chemical Engineering. Elsevier, 2018, Vol. 44, pp. 1951–1956. https://doi.org/10.1016/B978-0-444-64241-7.50320-7.
12. Yang, A.; Zhang, H.; Stewart, R.; Nguyen, K. Enhancing residential water end use pattern recognition accuracy using self-organizing maps and K-means clustering techniques: Autoflow v3.1. *Water* **2018**, *10*, 1221. https://doi.org/10.3390/w10091221.
13. Heydari, Z.; Stillwell, A. Comparative Analysis of Supervised Classification Algorithms for Residential Water End Uses. *Water Resources Research* **2024**, *60*, e2023WR036690. https://doi.org/10.1029/2023WR036690.
14. Pradeep, P.; Zhao, W.; Kowalski, M.; Bakeev, C. Disaggregating Household Water End-Uses: A Comparative Study between XGBoost and TabNet. In Proceedings of the 2024 6th International Conference on Data-driven Optimization of Complex Systems (DOCS). IEEE, 2024, pp. 385–392. https://doi.org/10.1109/DOCS63458.2024.10704250.
15. Mello, M.; Oliveira-Esquerre, K.; Botelho, G. Comparative Study of Similarity Measures Used to Classify Residential Water Flow Pattern of Low-Income Households in Salvador - Brazil. In *Computer Aided Chemical Engineering*; Elsevier, 2018; Vol. 44, pp. 1405–1410. https://doi.org/10.1016/B978-0-444-64241-7.50229-9.
16. Chávez-Flores, I.; Guerrero-Osuna, H.; Nava-Pintor, J.; García-Vázquez, F.; Luque-Vega, L.; Carrasco-Navarro, R.; Mata-Romero, M.; Lizarraga, J.; Castro-Tapia, S. A Feasibility Study of IoT-Based Classification of Residential Water-Use Activities in Storage Tank Systems: A Comparative Analysis of Decision Trees, Random Forest, SVM, KNN, and Neural Networks. *Technologies* **2026**, *14*, 223. https://doi.org/10.3390/technologies14040223.
17. Papatheodoulou, D.; Pavlou, P.; Vrachimis, S.; Malialis, K.; Eliades, D.; Theocharides, T. A Multi-label Time Series Classification Approach for Non-intrusive Water End-Use Monitoring. In Proceedings of the IFIP International Conference on Artificial Intelligence Applications and Innovations. Springer, 2022, pp. 53–66. https://doi.org/10.1007/978-3-031-08337-2_5.
18. Pastor-Jabaloyes, L.; Arregui, F.; Cobacho, R. Water end use disaggregation based on soft computing techniques. *Water* **2018**, *10*, 46. https://doi.org/10.3390/w10010046.
19. Charalampous, A.; Papadopoulos, A.; Hadjiyiannis, S.; Philimis, P. Towards hydro-informatics modernization with real-time water consumption classification. In Proceedings of the 2021 IEEE AFRICON. IEEE, 2021, pp. 1–6. https://doi.org/10.1109/AFRICON51333.2021.9570909.
20. Meyer, B.; Jacobs, H.; Ilemobade, A. Classifying household water use into indoor and outdoor use from a rudimentary data set: A case study in johannesburg, south africa. *Journal of Water, Sanitation and Hygiene for Development* **2021**, *11*, 423–431. https://doi.org/10.2166/washdev.2021.229.
21. Gourmelon, N.; Bayer, S.; Mayle, M.; Bach, G.; Bebber, C.; Munck, C.; Sosna, C.; Maier, A. Implications of experiment set-ups for residential water end-use classification. *Water* **2021**, *13*, 236. https://doi.org/10.3390/w13020236.
22. Bastidas Pacheco, C.; Horsburgh, J.; Beckwith, A.S., J. Impact of Data Temporal Resolution on Quantifying Residential End Uses of Water. *Water* **2022**, *14*, 2457. https://doi.org/10.3390/w14162457.
23. Sablica, L.; Grün, B.; Layeghy, S.; Dolnicar, S.; Portmann, M. EcoShower: Estimating shower duration using non-intrusive multi-modal sensor data via LSTM and Gated Transformer models. *Expert Systems with Applications* **2025**, *277*, 127202. https://doi.org/10.1016/j.eswa.2025.127202.
24. Günther, S.; Stingl, C.; Coroama, V.; Schöb, S.; Staake, T. Empowering personalized feedback on hot water usage: A field study with shower meters. In Proceedings of the Proceedings of the 35th Annual ACM Symposium on Applied Computing, 1 2020, pp. 763–766. https://doi.org/10.1145/3341105.3374053.
25. Keramati, M.; Azizi, E.; Momeni, H.; Hamidi Beheshti, M.; Bolouki, S. Non-intrusive load monitoring using water consumption patterns. In Proceedings of the 2020 28th Iranian Conference on Electrical Engineering (ICEE). IEEE, 2020, pp. 1–6. https://doi.org/10.1109/ICEE50131.2020.9260761.
26. Adrian Somontina, J.; Queen MacAbebe, E. A Non-Intrusive Water Consumption Monitoring System. In Proceedings of the 2020 IEEE Global Humanitarian Technology Conference (GHTC), 2020, pp. 1–6. https://doi.org/10.1109/GHTC46280.2020.9342898.
27. Pelekanos, N.; Kossieris, P.; Lykou, A.; Makropoulos, C. Disaggregating major water end-uses with minimal data: a machine learning and domain knowledge approach. *Urban Water Journal* **2025**, *22*, 436–446. https://doi.org/10.1080/1573062X.2025.2473046.
28. Laceda Taloma, R.; Comminiello, D.; Pisani, P.; Cuomo, F. UNet-WD: Deep Learning for Multi-Appliance Water Disaggregation. In Proceedings of the 2024 IFIP Networking Conference (IFIP Networking). IEEE, 2024, pp. 702–707. https://doi.org/10.23919/IFIPNetworking62109.2024.10619811.

29. Brunelli, C.; Pappacoda, G.; Zyrianoff, I.; Bononi, L.; Di Felice, M. Water Wastage Detection in Smart Homes Through IoT and Machine Learning. In Proceedings of the 2024 IEEE 21st Consumer Communications & Networking Conference (CCNC). IEEE, 2024, pp. 372–375. https://doi.org/10.1109/CCNC51664.2024.10454886.
30. Luk, M.H.; Yau, C.W.; Pong, P.; Lee, A.; Ngai, E.; Lui, K.S. High-Resolution Tap-Based IoT System for Flow Data Collection and Water End-Use Analysis. *IEEE Internet of Things Journal* **2022**, *9*, 22822–22835. https://doi.org/10.1109/JIOT.2022.3187999.
31. Vitter, J.S.; Webber, M.E. A non-intrusive approach for classifying residential water events using coincident electricity data. *Environmental modelling & software* **2018**, *100*, 302–313. https://doi.org/10.1016/j.envsoft.2017.11.029.
32. Forster, P.; Wallace, B.; Goubran, R.; Knoefel, F. Assessing activities of daily living by measuring residential water use with low cost thermistors. In Proceedings of the 2022 IEEE International Symposium on Medical Measurements and Applications (MeMeA). IEEE, 2022, pp. 1–6. https://doi.org/10.1109/MeMeA54994.2022.9856541.
33. Cristiano, E.; Biddau, P.; Delogu, A.; Gandolfi, M.; Deidda, R.; Viola, F. Automatic detection of water consumption temporal patterns in a residential area in Northen Italy. *Water Resources Management* **2024**, *38*, 6213–6228. https://doi.org/10.1007/s11269-024-03956-z.
34. Somontina, J.A.B.; Garcia, F.C.C.; Macabebe, E.Q.B. Water consumption monitoring with fixture recognition using random forest. In Proceedings of the TENCON 2018-2018 IEEE Region 10 Conference. IEEE, 2018, pp. 0663–0667. https://doi.org/10.1109/TENCON.2018.8650112.
35. Gross, M.P.; Taormina, R.; Cominola, A. A Machine Learning-based framework and open-source software for Non Intrusive Water Monitoring. *Environmental Modelling & Software* **2025**, *183*, 106247. https://doi.org/10.1016/j.envsoft.2024.106247.
36. Attallah, N.A.; Horsburgh, J.S.; Bastidas Pacheco, C.J. An open-source, semisupervised water end-use disaggregation and classification tool. *Journal of Water Resources Planning and Management* **2023**, *149*, 04023024. https://doi.org/10.1061/JWRMD5.WRENG-5444.
37. Arsene, D.; Predescu, A.; Truică, C.O.; Apostol, E.S.; Mocanu, M.; Chiru, C. Clustering Consumption Activities in a Water Monitoring System. In Proceedings of the 2022 IEEE International Conference on Automation, Quality and Testing, Robotics (AQTR). IEEE, 2022, pp. 1–6. https://doi.org/10.1109/AQTR55203.2022.9801952.
38. Obringer, R.; Nateghi, R.; Ma, Z.; Kumar, R. Improving the Interpretation of Data-Driven Water Consumption Models via the Use of Social Norms. *Journal of Water Resources Planning and Management* **2022**, *148*, 04022065. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001611.
39. Lee, D.; Derrible, S. Predicting Residential Water Demand with Machine-Based Statistical Learning. *Journal of Water Resources Planning and Management* **2020**, *146*, 04019067. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001119.
40. Zhang, J.; Savic, D.; Xu, Q.; Liu, K.; Qiang, Z. Poisson rectangular pulse (PRP) model establishment based on uncertainty analysis of urban residential water consumption patterns. *Environmental Science and Ecotechnology* **2024**, *18*, 100317. https://doi.org/10.1016/j.ese.2023.100317.
41. Sabzchi-Dehkharghani, H.; Majnooni-Heris, A.; Fakherifard, A.; Yegani, R. Estimation of household water consumption pattern in a metropolitan area taking the impact of the COVID-19 pandemic. *International Journal of Environmental Science and Technology* **2023**, *20*, 3161–3176. https://doi.org/10.1007/s13762-023-04761-8.
42. Zhang, Y.; Zhu, Y.; Li, H.; Wang, L.; Zhang, L.; Ding, H.; Wang, H. Quantifying the Impact of Climate Change on Household Water Use in Mega Cities: A Case Study of Beijing, China. *Sustainability* **2025**, *17*, 5628. https://doi.org/10.3390/su17125628.
43. Xia, S.; Zhu, H.; Zhang, N.; Li, Y.; Zhou, C. A dual-feature channel deep network with adaptive variable weight reconstruction for urban water demand prediction. *Sustainable Cities and Society* **2025**, *119*, 106118. https://doi.org/10.1016/j.scs.2024.106118.
44. Kim, J.; Lee, H.; Lee, M.; Han, H.; Kim, D.; Kim, H. Development of a Deep Learning-Based Prediction Model for Water Consumption at the Household Level. *Water* **2022**, *14*, 1512. https://doi.org/10.3390/w14091512.
45. Lagang, R.; Jayoma, J. IoT-Based Real-Time Water Consumption Monitoring and Forecasting Using Machine Learning. In Proceedings of the 2025 14th International Conference on Networks, Communication and Computing (ICNCC). IEEE, 2025, pp. 191–197. https://doi.org/10.1109/ICNCC68912.2025.00037.
46. Nasser, A.; Rashad, M.; Hussein, S. A Two-Layer Water Demand Prediction System in Urban Areas Based on Micro-Services and LSTM Neural Networks. *IEEE access* **2020**, *8*, 147647–147661. https://doi.org/10.1109/ACCESS.2020.3015655.
47. Marsili, V.; Mazzoni, F.; Alvisi, S.; Franchini, M. From Pressure to Water Consumption: Exploiting High-Resolution Pressure Data to Investigate the End Uses of Water. *Water Resources Management* **2024**, *38*, 4969–4985. https://doi.org/10.1007/s11269-024-03898-6.
48. Saganowski, L.; Andrysiak, T. Prediction of Water Usage for Advanced Metering Infrastructure Network with Intelligent Water Meters. In Proceedings of the Computational Intelligence in Security for Information Systems Conference. Springer, 2023, pp. 122–131. https://doi.org/10.1007/978-3-031-42519-6_12.
49. Kamau, S.; Waruguru, M. Predicting Domestic Water Consumption in Urban Areas Using Smart Water Meter Data. In Proceedings of the 2025 IEEE 4th International Conference on Computing and Machine Intelligence (ICMI). IEEE, 2025, pp. 1–6. https://doi.org/10.1109/ICMI65310.2025.11141211.

50. Maussner, C.; Teppan, E. Aggregated Dataset vs. Ensemble Learning for Spatial Transferability in Water Demand Forecasting. In Proceedings of the 2025 IEEE 37th International Conference on Tools with Artificial Intelligence (ICTAI). IEEE, 2025, pp. 1168–1174. https://doi.org/10.1109/ICTAI66417.2025.00170.
51. Wang, C.; Li, Z.; Ni, X.; Shi, W.; Zhang, J.; Bian, J.; Liu, Y. Residential water and energy consumption prediction at hourly resolution based on a hybrid machine learning approach. *Water research* **2023**, *246*, 120733. https://doi.org/10.1016/j.watres.2023.120733.
52. De Souza, N.; dos Santos Miranda, I.D.; Khun, A.; Romeiro, L.d.A.W.; Fontes, C.H.; de Castro Lima, A.C. Development of an acoustic flowmeter for low flow rates. *Flow Measurement and Instrumentation* **2023**, *91*, 102368. https://doi.org/10.1016/j.flowmeasinst.2023.102368.
53. Faiz, M.; Daniel, A. Wireless sensor network based distribution and prediction of water consumption in residential houses using ANN. In Proceedings of the International Conference on Internet of Things and Connected Technologies. Springer, 2021, pp. 107–116. https://doi.org/10.1007/978-3-030-94507-7_11.
54. Zhakiyev, N.; Omirgaliyev, R.; Bapiyev, I.; Baisakalova, N.; Tankeyev, S. System for Water and Electricity Consumption Prediction in Smart Cities Using ML. In Proceedings of the 2023 IEEE International Conference on Smart Information Systems and Technologies (SIST). IEEE, 2023, pp. 278–282. https://doi.org/10.1109/SIST58284.2023.10223522.
55. Rubiños, M.; Jove, E.; García-Ordás, M.T.; Abelha, A.; Alaiz-Moretón, H. Unsupervised AI-based water consumption classification from time series data. *Logic Journal of the IGPL* **2026**, *34*, jzaf082. https://doi.org/10.1093/jigpal/jzaf082.
56. Rahim, M.S.; Anh Nguyen, K.; Stewart, R.A.; Giurco, D.; Blumenstein, M. Predicting household water consumption events: Towards a personalised recommender system to encourage water-conscious behaviour. In Proceedings of the 2019 International Joint Conference on Neural Networks (IJCNN). IEEE, 2019. https://doi.org/10.1109/IJCNN.2019.8851868.
57. Bethke, G.; Cohen, A.; Stillwell, A. Emerging investigator series: Disaggregating residential sector high-resolution smart water meter data into appliance end-uses with unsupervised machine learning. *Environmental Science: Water Research & Technology* **2021**, *7*, 487–503. https://doi.org/10.1039/d0ew00724b.
58. Rahim, M.; Nguyen, K.; Stewart, R.; Ahmed, T.; Giurco, D.; Blumenstein, M. A clustering solution for analyzing residential water consumption patterns. *Knowledge-Based Systems* **2021**, *233*, 107522. https://doi.org/10.1016/j.knosys.2021.107522.
59. Niazmardi, S.; Sadrykia, M.; Rezazadeh, M. Analysis of spatiotemporal household water consumption patterns and their relationship with meteorological variables. *Urban Climate* **2023**, *52*, 101707. https://doi.org/10.1016/j.uclim.2023.101707.
60. Bermejo-Martín, G.; Rodríguez-Monroy, C.; Núñez-Guerrero, Y. Water consumption range prediction in Huelva's households using classification and regression trees. *Water* **2021**, *13*, 506. https://doi.org/10.3390/w13040506.
61. Abu-Bakar, H.; Williams, L.; Hallett, S. An empirical water consumer segmentation and the characterisation of consumption patterns underpinning demand peaks. *Resources, Conservation and Recycling* **2021**, *174*, 105792. https://doi.org/10.1016/j.resconrec.2021.105792.
62. Yang, A.; Zhang, H.; Stewart, R.; Nguyen, K. Water end use clustering using hybrid pattern recognition techniques - Artificial Bee Colony, Dynamic Time Warping and K-Medoids clustering. *International Journal of Machine Learning and Computing* **2018**, *8*, 483–487. https://doi.org/10.18178/ijmlc.2018.8.5.733.
63. Rahim, M.; Nguyen, K.; Stewart, R.; Giurco, D.; Blumenstein, M. Advanced household profiling using digital water meters. *Journal of environmental management* **2021**, *288*, 112377. https://doi.org/10.1016/j.jenvman.2021.112377.
64. Abu-Bakar, H.; Williams, L.; Hallett, S. Contextualising household water consumption patterns in England: A socio-economic and socio-demographic narrative. *Cleaner and Responsible Consumption* **2023**, *8*, 100104. https://doi.org/10.1016/j.clrc.2023.100104.
65. Khan, H.; Stillwell, A. Patterns tell human stories: towards connecting residential water use to occupant behavior in a permanent supportive housing context. *Environmental Research: Infrastructure and Sustainability* **2025**, *5*, 045011. https://doi.org/10.1088/2634-4505/ae1e9c.
66. Arias-Garcia, J.; Cárdenas-Peña, D.; Orozco-Gutiérrez, A.; Garcia-Arias, H.; Guerrero-Erazo, J. Graph-Based Clustering of Urban Water Consumption Profiles via Adaptive Attention and Multi-Relational Topologies. *Water* **2026**, *18*, 1272. https://doi.org/10.3390/w18111272.
67. Lall, A.; Terala, A.; Goyal, A.; Chaudhari, S.; Rajan, K.; Chouhan, S. Behavioural Analysis of Water Consumption Using IoT-Based Smart Retrofit Meter. *IEEE Access* **2024**, *12*, 113597–113607. https://doi.org/10.1109/ACCESS.2024.3436889.
68. Naseri, M.; Bernosky, G.; Mayer, P.; Marston, L. Patterns and Predictors of Residential Indoor Water Use Across Major US Cities. *Earth's Future* **2025**, *13*, e2024EF005467. https://doi.org/10.1029/2024EF005467.
69. Arsene, D.; Predescu, A.; Truică, C.O.; Apostol, E.S.; Mocanu, M. Decision support strategies for household water consumption behaviors based on advanced recommender systems. *Water* **2023**, *15*, 2550. https://doi.org/10.3390/w15142550.
70. Berlotti, M.; Di Grande, S.; Cavalieri, S.; Gueli, R. Modelling and Clustering Patterns from Smart Meter Data in Water Distribution Systems. In Proceedings of the ICEIS (1), 2025, pp. 691–698. https://doi.org/10.5220/0013200500003929.
71. Guo, H.; Liu, X.; Zhang, Q. Identifying daily water consumption patterns based on K-means Clustering, Agglomerative Hierarchical Clustering, and Spectral Clustering algorithms. *AQUA—Water Infrastructure, Ecosystems and Society* **2024**, *73*, 870–887. https://doi.org/10.2166/aqua.2024.294.

72. Srinivasan, R.; Vimala Devi, K.; Praveenraj, D.W.; Venkatasuvrananian, S.; Subramani, K.; Prasanth, V.; Gaddala, B.R. IoT-Driven Dynamic Behavior Intervention Model for Sustainable Hygiene Practices: Insights from Household Water Consumption. In Proceedings of the International Conference on Artificial Intelligence and its Application. Springer, 2023, pp. 136–154. https://doi.org/10.1007/978-3-031-84394-5_11.
73. Quinto, C.; Insuasti, J.; Simbaña, M.; Palma, P.; Albarracin, W.; Egas, P. IoT-Based Electronic System for Real-Time Monitoring and AI-Driven Analysis of Residential Water Consumption. *Electronics* **2026**, *15*, 3104. https://doi.org/10.3390/electronics15143104.
74. Attallah, N.; Horsburgh, J.; Beckwith, Jr., A.S.; Tracy, R. Residential water meters as edge computing nodes: Disaggregating end uses and creating actionable information at the edge. *Sensors* **2021**, *21*, 5310. https://doi.org/10.3390/s21165310.
75. Di Mauro, A.; Santonastaso, G.; Venticinque, S.; Di Nardo, A. Open Datasets and IoT Sensors for Residential Water Demand Monitoring at the End-Use Level: A Pilot Study Site in Naples (Italy). In *Resilient Water Management Strategies in Urban Settings: Innovations in Decentralized Water Infrastructure Systems*; Springer, 2022; pp. 47–76. https://doi.org/10.1007/978-3-030-95844-2_4.
76. Pastor-Jabaloyes, L.; Arregui, F.; Cobacho, R. A filtering algorithm for high-resolution flow traces to improve water end-use analysis. *Water Supply* **2019**, *19*, 451–462. https://doi.org/10.2166/ws.2018.090.
77. Luciani, C.; Casellato, F.; Alvisi, S.; Franchini, M. Green Smart Technology for Water (GST4Water): Water loss identification at user level by using smart metering systems. *Water* **2019**, *11*, 405. https://doi.org/10.3390/w11030405.
78. Oliveira-Esquerre, K.; Mello, M.; Botelho, G.; Deng, Z.; Koushanfar, F.; Kiperstok, A. Water end-use consumption in low-income households: Evaluation of the impact of preprocessing on the construction of a classification model. *Expert Systems with Applications* **2021**, *185*, 115623. https://doi.org/10.1016/j.eswa.2021.115623.
79. Parveen, M.; Lakshana, S.; Saranya, P.; Avanthika, S.; Ali, M. Predictive Modeling for Water Anomaly Detection Using Machine Learning. In Proceedings of the 2025 International Conference on Computing and Communication Technologies (ICCCT). IEEE, 2025, pp. 1–5. https://doi.org/10.1109/ICCCT63501.2025.11019440.
80. Saganowski, L.; Andrysiak, T. Smart Water Meter Network Anomaly and Failure Detection System. In Proceedings of the International Conference on EUropean Transnational Education. Springer, 2024, pp. 35–44. https://doi.org/10.1007/978-3-031-75016-8_4.
81. Jasiūnas, Z.; Braz Ferreira, J.; Julião, T.; Cecílio, J.; Carrilho da Graça, G.; Ferreira, P. Household Laundry Appliance Resource Consumption and Operation Dataset. *Scientific Data* **2026**. https://doi.org/10.1038/s41597-026-07361-6.
82. Herrera-Santos, J.; Márquez-Sánchez, S.; Alonso-Rollán, S.; Chamoso-Santos, P. Edge AI Smart Water IoT Device for Domestic Consumption Classification. In Proceedings of the International Symposium on Distributed Computing and Artificial Intelligence. Springer, 2025, pp. 233–242. https://doi.org/10.1007/978-3-032-04160-9_21.
83. del Pilar Villacís-Guerrero, J.; Cunalata-Paredes, D.Y.; Bonilla-Villacís, J.R.; Soria, A.; Avilés-Castillo, F. Residential water consumption monitoring system using IoT and MQTT communication. In Proceedings of the International Conference on Computational Science and Its Applications. Springer, 2022, pp. 518–533. https://doi.org/10.1007/978-3-031-10548-7_38.
84. Soh, Z.H.C.; Isa, I.S.; Ahmad, F.; Daud, K.; Yahaya, S.Z.; Ismail, A.P.; Abdullah, S.A.C. IoT based water consumption management system via low power wide area network. In Proceedings of the AIP Conference Proceedings. AIP Publishing LLC, 2024, Vol. 2898, p. 020003. https://doi.org/10.1063/5.0192453.
85. Ali, A.; Salah, M. A case study of iot-based water-energy nexus monitoring platform for household applications in smart cities. In Proceedings of the 2023 IEEE Jordan International Joint Conference on Electrical Engineering and Information Technology (JEEIT). IEEE, 2023, pp. 1–6. https://doi.org/10.1109/JEEIT58638.2023.10185836.
86. Carratù, M.; Iacono, S.D.; Di Leo, G.; Gallo, V.; Liguori, C.; Pietrosanto, A. A novel image processing technique based on deep learning for water consumption detection. In Proceedings of the 2022 IEEE International Instrumentation and Measurement Technology Conference (I2MTC). IEEE, 2022, pp. 1–6. https://doi.org/10.1109/I2MTC48687.2022.9806636.
87. Mohamed, N.E.D.M.; Akwah, O.E.; Mohamed, A.N.; El-Dakroury, M.M. AI-Driven Smart Water Flow Meter System for Real-Time Water Monitoring and Probabilistic Leakage Detection. In Proceedings of the 2025 7th Novel Intelligent and Leading Emerging Sciences Conference (NILES). IEEE, 2025, pp. 457–462. https://doi.org/10.1109/NILES68063.2025.11231824.
88. Bharudin, M.S.A.; Zainuddin, A.A.; Roslee, A.M.; Razak, N.A.A.; Abd Halim, M.H.F.; Saifudin, N.N.M. Comprehensive IoT-Based Water Management System: Cloud Integration for Residential Conservation. In Proceedings of the 2024 IEEE 12th Region 10 Humanitarian Technology Conference (R10-HTC). IEEE, 2024, pp. 1–6. https://doi.org/10.1109/R10-HTC59322.2024.10778751.
89. Amora, D.J.A.; Janapin, M.A.V.; Calayag, B.A.M.; Rioflorido, C.L.P.P.; Estur, N.M.; Villegas, P.A.L. Design of a household consumption based water leak detection system utilizing machine learning algorithm. In Proceedings of the 2022 IET International Conference on Engineering Technologies and Applications (IET-ICETA). IEEE, 2022, pp. 1–2. https://doi.org/10.1109/IET-ICETA56553.2022.9971564.
90. Roslan, M.Y.H.; Rahman, F.Y.A.; Mohamad, R.; Shahbudin, S. Development and Evaluation of an IoT-Based Home Water Usage Monitoring System Using LoRa and ESP32. In Proceedings of the 2025 IEEE 16th Control and System Graduate Research Colloquium (ICSGRC). IEEE, 2025, pp. 111–114. https://doi.org/10.1109/ICSGRC65918.2025.11159838.

91. Tsao, Y.C.; Kuo, Y.W.; Wu, C.C.; Tsai, Y.T.; Hsu, C.; Ho, L.; Wang, H.C. Implementation and design of water flow meter of smart home integrated with environment monitor system. In Proceedings of the 2022 IEEE 4th Eurasia Conference on Biomedical Engineering, Healthcare and Sustainability (ECBIOS). IEEE, 2022, pp. 126–131. https://doi.org/10.1109/ECBIOS54627.2022.9945010.
92. Varghese, L.J.; Devanath, V.; Kishore, V.; Poornima, R.; Jacob, S.S. IoT Based Smart Water Meter for Domestic Utility. In Proceedings of the 2025 International Conference on Inventive Computation Technologies (ICICT). IEEE, 2025, pp. 1601–1608. https://doi.org/10.1109/ICICT64420.2025.11005058.
93. Ahamed, I.; Ali, M.L.; Salehin, N. IoT-based Smart Water Consumption Monitoring System for Residential Complex. In Proceedings of the 2024 2nd International Conference on Information and Communication Technology (ICICT). IEEE, 2024, pp. 46–50. https://doi.org/10.1109/ICICT64387.2024.10839689.
94. Cabrera, G.H.C.; Chipana, G.J.F.; Chambilla, T.R.B.; Cahua, A.D.M.; De La Cruz, S.E.C.; Ponce, G.R.V. IoT-Smart Water Monitoring Module for Home Connection for Pattern Identification Based on ESP32-Grafana. In Proceedings of the 2025 IEEE Colombian Caribbean Conference (C3). IEEE, 2025, pp. 1–6. https://doi.org/10.1109/C366505.2025.11340073.
95. Marathe, A.; Lodha, A.; Lolage, O.; Lodha, P.; Herald, L. Smart Water Management System for Housing Societies. In Proceedings of the 2024 2nd International Conference on Emerging Trends in Engineering and Medical Sciences (ICETEMS). IEEE, 2024, pp. 457–461. https://doi.org/10.1109/ICETEMS64039.2024.10965023.
96. Akash, S.; Adwaith, J.; Adish, B.; AK, A.; et al. Smartdrop–A Smart Domestic Water Management and Alert System. In Proceedings of the 2026 International Conference on Computational Robotics, Testing and Engineering Evaluation (ICCRTEE). IEEE, 2026, pp. 1–6. https://doi.org/10.1109/ICCRTEE68719.2026.11566579.
97. Boudhaouia, A.; Wira, P. Water consumption analysis for real-time leakage detection in the context of a smart tertiary building. In Proceedings of the 2018 International Conference on Applied Smart Systems (ICASS). IEEE, 2018, pp. 1–6. https://doi.org/10.1109/ICASS.2018.8651976.
98. Ali, A.; Rahman, M.; Siddique, M.; Galib, S.; Nashiry, A. Design of an automatic rooftop water tank filling system and measurement of consumed water for home appliance. *International Journal of Automation and Smart Technology* **2023**, *13*, 1–9. https://doi.org/10.5875/ausmt.v13i1.2371.
99. Torres-Gutierrez, J.L.; Castañeda-Miranda, C.L.; Martínez-Blanco, M.d.R.; Guerrero-Osuna, H.A.; Jiménez-Díaz, G.; Espinoza-García, G.; Moreno-Lucio, M.; Ibarra-Pérez, T.; Solís-Sánchez, L.O. Development and Implementation of a Smart Water Metering and Monitoring System for Homes with Intermittent Water Supply. *Technologies* **2026**, *14*, 135. https://doi.org/10.3390/technologies14020135.
100. Ünsal, B.; Akselli, B.; Sacı, Ş.; Aksel, E. Initial results on the flow dynamics of household water consumption. In Proceedings of the Proc. 18th Int. Flow Measurement Conf.(Flomeko), 2019, pp. p–6.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.