



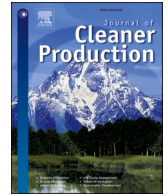
Household water consumption patterns revealed through high-resolution fixture-level monitoring in a Swedish living lab

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Household water consumption patterns revealed through high-resolution fixture-level monitoring in a Swedish living lab

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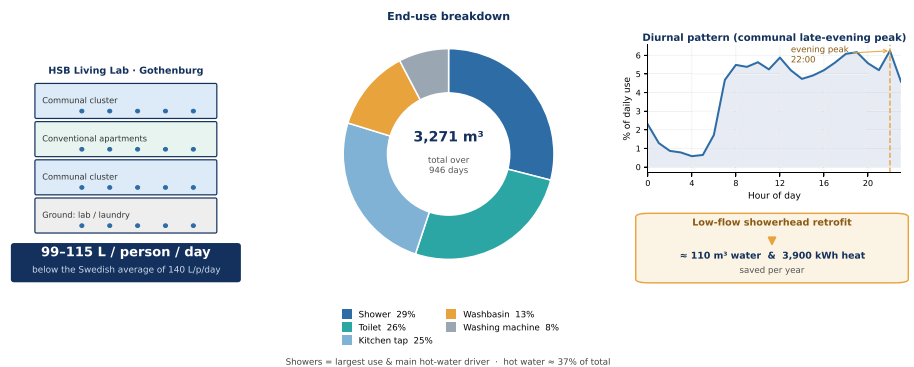
HIGHLIGHTS

- Three years of fixture-level metering of hot and cold water in a Swedish living lab.
- Water use was 99 to 115 L per person per day, below the Swedish average of 140.
- Showers were the largest end use and the main driver of hot-water heating energy.
- Low-flow showerheads would save about 110 cubic metres and 3900 kWh per year.
- Shared and conventional homes in one building show which findings transfer.

GRAPHICAL ABSTRACT

Household water use revealed by 3 years of fixture-level monitoring in a Swedish living lab

Hot & cold water metered separately at every fixture · ~30–35 residents · communal + conventional housing under one roof



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ABSTRACT

Detailed knowledge of household water use, at the level of individual fixtures, at high time resolution and in shared housing, remains scarce, limiting the design of water- and energy-efficient buildings. This study draws on a rare three-year dataset from the HSB Living Lab, a purpose-built residential facility in Gothenburg, Sweden combining two housing typologies: communal shared-living clusters and conventional self-contained apartments. Every fixture was metered individually by 214 m at 1-litre resolution and a fixed 10-min reporting interval, with hot and cold supply lines metered separately, allowing consumption to be characterised from 10 min to three years, decomposed by end use and compared between housing types within one building, climate and metering system. Residential consumption was 94–110 L/person/day, below the Swedish average of 140. Showers were the largest end use (30.5%); 38.3% of residential water and 64.4% of shower water were hot. The building's most distinctive features, a high shared-space share and a late-evening peak, proved specific to the communal clusters, whereas the conventional apartments behaved much like mainstream housing, clarifying which findings transfer beyond student living. Three results apply directly to water–energy management: peak-demand factors for system sizing (peak hour factor 1.53; daily peak-to-mean 4.40, or 2.49 on a 99th-percentile-day basis); a ranking of end uses by coupled water–energy intensity identifying showers as the highest-leverage retrofit target, where a

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low-flow measure would save an estimated 110 m³ of water and 3900 kWh per year; and evidence that hybrid metering and billing suits shared housing, where much consumption is collective.

1. Introduction

The increasing strain on global freshwater resources, driven by population growth, urbanization, and climate change, has elevated the importance of understanding and managing domestic water consumption (Grafton et al., 2011; House-Peters and Chang, 2011). Residential water use accounts for a substantial share of total municipal water demand in developed countries, yet the determinants of aggregate demand are far better characterised than the way water is actually used at the level of individual fixtures (Arbués et al., 2003; Fielding et al., 2012). Two gaps are particularly relevant: high-frequency, fixture-level monitoring sustained over multiple years remains rare, and water-use patterns in shared-housing arrangements are seldom characterised. Recent worldwide reviews of residential end uses (Mazzoni et al., 2023) and of residential hot-water consumption (Mazzoni et al., 2026) synthesise a large but heterogeneous evidence base and highlight these same shortfalls. This knowledge gap hinders the development of effective conservation strategies and the design of water-efficient buildings and infrastructure.

In Sweden, household water consumption is estimated at approximately 140 L per person per day, placing it within the optimal access category as defined by the World Health Organization (Howard and Bartram, 2003). While Sweden has not historically faced severe water scarcity, localized shortages have become increasingly frequent, particularly during summer months, highlighting the vulnerability of even water-rich nations to changing climatic conditions (Sauri, 2013). Beyond volumetric concerns, household water use carries significant environmental implications. The production and distribution of drinking water generates approximately 40 g CO₂ per cubic meter, while the energy required to heat domestic hot water contributes roughly 2.6 kg equivalent CO₂ per cubic meter when considering the Swedish energy mix (Swedish Energy Agency, 2020). Given that hot water production accounts for a substantial fraction of household energy consumption, understanding the balance between hot and cold water use across different fixtures is essential for both water and energy conservation planning.

Traditional approaches to monitoring household water consumption typically rely on aggregate meter readings at the building or household level, providing limited insight into end-use behaviors (Cardell-Oliver, 2013). The emergence of smart metering technologies has created new opportunities for disaggregated water consumption analysis, enabling researchers to identify specific fixtures, temporal patterns, and behavioral signatures (Cominola et al., 2019; Davies et al., 2014). Several studies have demonstrated the potential of smart meter data for leak detection, demand forecasting, and behavioral interventions (Britton et al., 2013; DeOreo et al., 2016; Willis et al., 2011). The landmark Residential End Uses of Water Study (REUWS) in North America (DeOreo et al., 2016) established benchmark distributions for fixture-level consumption, but was conducted in a markedly different climatic and cultural context than Northern Europe.

However, datasets combining high temporal resolution (sub-hourly readings), fixture-level disaggregation, and extended monitoring periods remain rare in the literature (Avni et al., 2015). Most existing smart meter studies either cover short time periods (typically weeks to months), monitor only aggregate consumption, or focus on a small number of households. Critically, few studies provide sufficient duration to assess the stability of seasonal patterns or to distinguish persistent behavioral differences from transient fluctuations. Furthermore, there is limited research on water consumption patterns in shared housing arrangements, such as student housing with communal facilities, which represent an increasingly common urban living model (Hussien et al.,

2016).

A key analytical gap in the existing literature concerns intra-building heterogeneity. While studies have documented variation between households, the degree to which consumption varies across apartments within a single building, and across different residential cluster configurations, remains largely unexplored. Understanding this heterogeneity is essential for infrastructure sizing, demand management, and the design of targeted behavioral interventions (Jorgensen et al., 2014). Multi-year datasets at fixture resolution provide the unique ability to decompose variance into temporal, spatial, and end-use components, offering insights unattainable from aggregate monitoring.

Living laboratories offer a unique research environment for studying resource consumption in residential settings. The HSB Living Lab (hereafter referred to as the Habitation Lab, following the classification of Knutsson et al. (Knutsson and Marx, 2016)) in Gothenburg, Sweden, is a purpose-built third-generation living lab where approximately 30 tenants live permanently while their resource consumption is monitored through an extensive sensor network comprising over 2000 sensors. The building was constructed in 2016 as a joint venture between Chalmers University of Technology and HSB, a major Swedish housing corporation, with the explicit goal of facilitating sustainable innovation in the built environment (Femenias and Hagbert, 2013; Knutsson and Marx, 2016). The plumbing system was specifically designed to allow individual metering of each water consumption point, including every shower, faucet, toilet, and washing machine, for both hot and cold water. Importantly, and in contrast to the impression of a homogeneous student-studio block, the building deliberately combines two housing typologies, communal shared-living clusters and conventional one-to-four-room apartments (Section 2.1), which allows a within-building comparison of housing types that bears directly on the transferability of the findings.

This study leverages the unique capabilities of the Habitation Lab to present a rare multi-year, fixture-level household water consumption dataset. The objectives are: (1) to characterize water consumption patterns at the fixture level across multiple temporal scales; (2) to quantify intra-building heterogeneity, relate it to housing typology, and assess its implications for infrastructure design; (3) to examine the energy-water nexus through detailed hot and cold water analysis and to quantify the savings achievable from a fixture-level efficiency intervention; and (4) to evaluate the statistical significance and robustness of observed differences across residential clusters and temporal periods.

2. Materials and methods

Fig. 1 summarises the overall methodology, organised into the three stages used in this section: data collection (Sections 2.1–2.2), data processing (Section 2.3) and statistical analysis (Section 2.4), together with the spatial and temporal scales spanned by the analysis.

2.1. Study site

The HSB Living Lab (Habitation Lab) is a four-story modular residential building with a footprint area of approximately 400 m², located on the Chalmers University campus in Gothenburg, Sweden (57.69 N, 11.98 E). Construction commenced in 2015, with tenants moving in on June 1, 2016 (Knutsson and Marx, 2016). The ground floor houses a social laundry studio, a co-creation laboratory for research workshops, and a data and communications centre. The three residential floors above are organized into nine monitored residential clusters. A residential cluster is defined here as a group of dwelling units that share a structural module and, in the communal case, share kitchen and

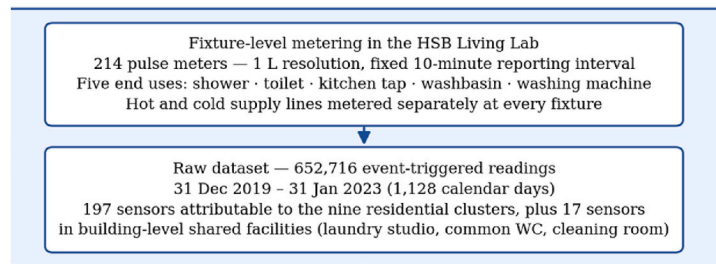
bathroom facilities; this definition is used consistently throughout the paper and underpins the cluster-level analyses in Sections 3.6 and 3.7. The nine clusters fall into two distinct housing typologies (Table 1). The communal shared-living clusters (gemensamhetsboende; clusters C1, C2, C8 and C9, on the second and fourth floors) each provide private rooms of approximately 13 m² with a kitchenette and toilet, around a shared kitchen/social area and two shared bathrooms; these clusters contain 23 of the 28 monitored dwelling units. The conventional self-contained apartments (clusters C3–C7, on the third floor) are complete flats with private kitchen and bathroom, ranging from one room plus kitchen (1 RoK, ~32–39 m²) through three RoK (~82.5 m²) to four RoK (~83 m²). In addition to the nine clusters, the ground-floor social laundry studio and cleaning room provide residential functions but belong to no single cluster. Two ground-floor common washrooms primarily serve meeting and conference activities; they are classified as non-residential and reported separately (Section 2.2 and Table 1).

Occupancy is not metered directly; based on the number of private rooms (one communal room is a non-occupied show room) and apartment sizes, the building houses an estimated 30–35 tenants, primarily students and guest researchers, with typical tenancy durations of 6 to 24 months. This occupancy range is used consistently for all per-capita estimates in this paper, and the dual typology is exploited in Section 3.6 to compare communal and conventional housing within the same building, climate and metering system.

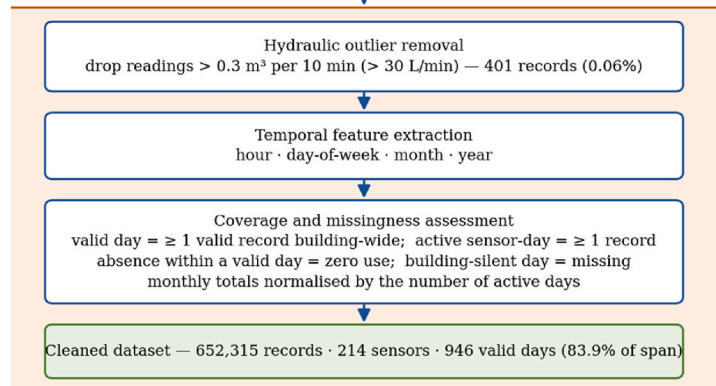
2.2. Data collection

The plumbing system was designed to allow individual water metering of each consumption point. The installed meters are pulse-counting type with a resolution of 1 L and a fixed reporting interval of 10 min. Meter accuracy is specified at $\pm 2\%$ at nominal flow rates. A record is written by the logging system only when at least one pulse is

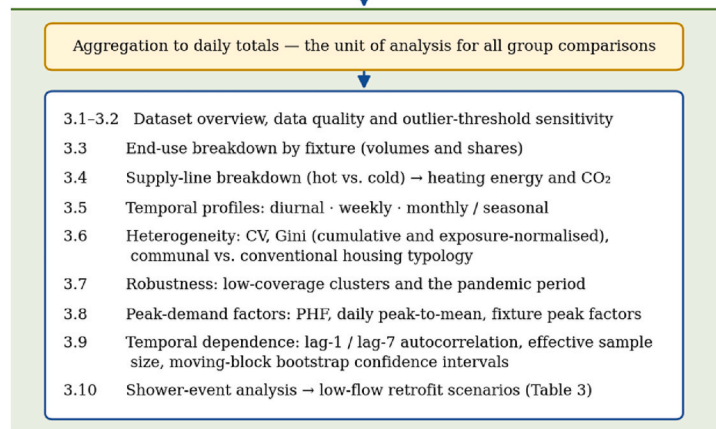
1. DATA COLLECTION (2.1–2.2)



2. DATA PROCESSING (2.3)



3. STATISTICAL ANALYSIS (2.4)



Application

Low-flow showerhead intervention scenarios (20 / 30 / 40% shower-volume reduction) → water, heating energy and CO₂ saved

Scales of analysis

Spatial
 fixture (214 meters)
 → room
 → dwelling unit (28)
 → residential cluster (9)
 → building

Temporal
 10-min reading → hour
 → day → week
 → month → 3-year period

Inferential tests (daily totals)

Kruskal–Wallis (ϵ^2)
 across fixtures / clusters

Friedman blocked by date
 (Kendall's W) — repeated
 measures across dates

Mann–Whitney U
 (rank-biserial r)

Fig. 1. Methodological overview, organised into data collection (Sections 2.1–2.2), data processing (Section 2.3) and statistical analysis (Section 2.4). The cleaned meter dataset contains 652,315 records from 214 sensors; residential analyses retain 635,899 records from 208 sensors after excluding six sensors in meeting/conference washrooms, while the social laundry studio and cleaning room remain included. The right-hand panels state the spatial and temporal scales, inferential tests and intervention scenarios.

Table 1

Residential clusters, residential shared facilities and non-residential ground-floor washrooms (totals over the 946-day cleaned period). The residential analytical boundary comprises 197 sensors in the nine residential clusters plus 11 sensors in the social laundry studio and cleaning room (208 sensors in total). Six sensors in two meeting/conference washrooms are reported separately and excluded from residential analyses.

Cluster(s)	Typology	Dwelling	Units	Sensors	Data coverage	Total (m ³)
C1, C2, C8, C9	Communal (shared living)	13 m ² private room + shared kitchen/2 bathrooms	23	159	82–84%	1737
C3	Conventional apartment	3 RoK (~82.5 m ²)	1	8	77.2%	318
C4	Conventional apartment	1 RoK (~39 m ²)	1	7	62.6%	190
C5	Conventional apartment	1 RoK (~32 m ²)	1	7	28.6%	28
C6	Conventional apartment	3 RoK	1	8	77.0%	270
C7	Conventional apartment	4 RoK (~83 m ²)	1	8	83.8%	373
—	Residential shared facilities	Social laundry studio; cleaning room	—	11	—	194
Residential	Residential analytical total	Clusters + residential shared facilities	28	208	83.9%	3110
—	Non-residential building use	2 meeting/conference washrooms	—	6	—	161
All	Whole-building meter total		28	214	83.9%	3271

registered within a 10-min interval; intervals with no flow generate no record. The dataset is therefore event-triggered rather than a complete fixed panel and, by construction, contains no zero-valued readings. This property governs the interpretation of data coverage and is treated explicitly in Section 2.3.

A total of 214 sensors are installed. Of these, 197 lie inside the nine residential clusters and are attributable to a specific cluster and dwelling unit (Table 1). Of the remaining 17 ground-floor sensors, 10 meters the social laundry studio and one meters the cleaning room; both functions serve residents and are retained in the residential analyses. The other six sensors meter two common washrooms used primarily by meeting and conference activities. These six sensors are reported separately as non-residential building use and excluded from all residential volume, per-capita, end-use, hot-water and temporal analyses. Over the cleaned period, the laundry studio consumed 186.178 m³ (160.024 m³ at washing machines and 26.154 m³ at its washbasin), the cleaning room 7.449 m³, and the two non-residential washrooms 160.898 m³. The residential analytical dataset therefore covers 208 sensors: 197 cluster-attributed sensors and 11 residential shared-facility sensors. Five end-use categories are monitored: shower, toilet, kitchen tap, washbasin and washing machine. Both hot and cold water consumption are measured separately at each point; where a fixture is fed by a mixer, the hot and cold supply lines are metered upstream of the mixer. Table 2 inventories all 214 installed sensors and identifies the six excluded non-residential washroom sensors in its caption.

2.3. Data processing

The raw dataset was processed through a systematic cleaning pipeline (Fig. 1). Field labels for fixture types and room categories are stored in Swedish in the source system and are reported in English throughout this paper (e.g., “Dusch” = shower); this is a reporting convention rather than a step of the scientific method, and it is therefore not shown as a processing stage in Fig. 1. The pipeline comprised three steps:

- Outlier detection used a hydraulically justified threshold. The maximum flow rate for a single residential fixture is approximately

Table 2

Sensor inventory by end use and water supply line (number of distinct installed sensors). The total of 214 comprises 208 sensors retained in residential analyses and six toilet/washbasin sensors in two ground-floor meeting/conference washrooms that are reported separately and excluded from residential analyses.

End use	Cold	Hot	Total
Washbasin	40	38	78
Kitchen tap	35	30	65
Toilet	36	0	36
Shower	13	11	24
Washing machine	8	3	11
Total	132	82	214

12 L/min (high-flow shower), an assumed (not measured) hydraulic bound that yields a maximum plausible 10-min consumption of about 120 L (0.12 m³). A conservative threshold of 0.3 m³ (300 L per 10 min, corresponding to a sustained flow rate of 30 L/min) was selected to account for potential simultaneous multi-fixture use while still flagging physically implausible readings. In the cleaned dataset the 99th percentile of individual readings is 0.045 m³ and the 99.9th percentile 0.104 m³, both well below this threshold. Sensitivity analysis showed that varying the threshold between 0.1 and 0.5 m³ changed total consumption by between −3.8% (at 0.1 m³) and +1.3% (at 0.5 m³) relative to the adopted threshold, and by less than 1% over the range 0.2–0.5 m³; the 0.3 m³ threshold removes 401 records (0.06% of the dataset).

- Temporal features (hour, day of week, month, year) were extracted from timestamps.
- Coverage and missingness were assessed using explicit definitions. Because records are event-triggered (Section 2.2), the absence of a record can mean either no water use or an interruption in logging, and the two must be separated. A valid day is a calendar day on which at least one sensor returned at least one valid record after cleaning; an active sensor-day is a (sensor, day) pair with at least one valid record; and a sensor is treated as operational between its first and its last valid record. On a valid day, a silent sensor is treated as zero use, because the logging chain is demonstrably functioning; on a day when no sensor anywhere in the building returned a record, all sensor-days of that day are treated as missing. Monthly and cluster totals were normalised by the number of active days so that differences in coverage do not propagate into temporal comparisons.

The final cleaned meter dataset contained 652,315 records. Applying the functional boundary described in Section 2.2 excluded 16,416 records from the six non-residential washroom sensors, leaving 635,899 records from 208 sensors for residential consumption analyses. Data-quality and coverage diagnostics below refer to the complete cleaned meter dataset unless stated otherwise. Of the 1128 calendar days in the monitoring window, 946 were valid days, giving a temporal coverage of 946/1128 = 83.9%; the remaining 182 days are dominated by three extended logging outages — 24 November 2021 to 16 February 2022 (85 days), 30 June to 19 August 2020 (51 days) and 1 September to 2 October 2022 (32 days) — with the balance made up of short gaps of one to five days (Fig. 2). Coverage at the level of individual sensors is necessarily lower and is not directly comparable: 123,449 active sensor-days were recorded, which is 62.1% of the 198,805 sensor-days that fall inside a sensor's operational window on a valid day. The remaining 37.9% are predominantly genuine zero-use days rather than data loss, since an individual washbasin, shower or washing machine is not used every day. For the same reason, the dataset should not be evaluated against a complete fixed panel of 214 × 1128 × 144 ≈ 34.8 million sensor-intervals: at a 1-litre pulse resolution a single fixture draws water in only a small minority of 10-min intervals, and the 652,315 records

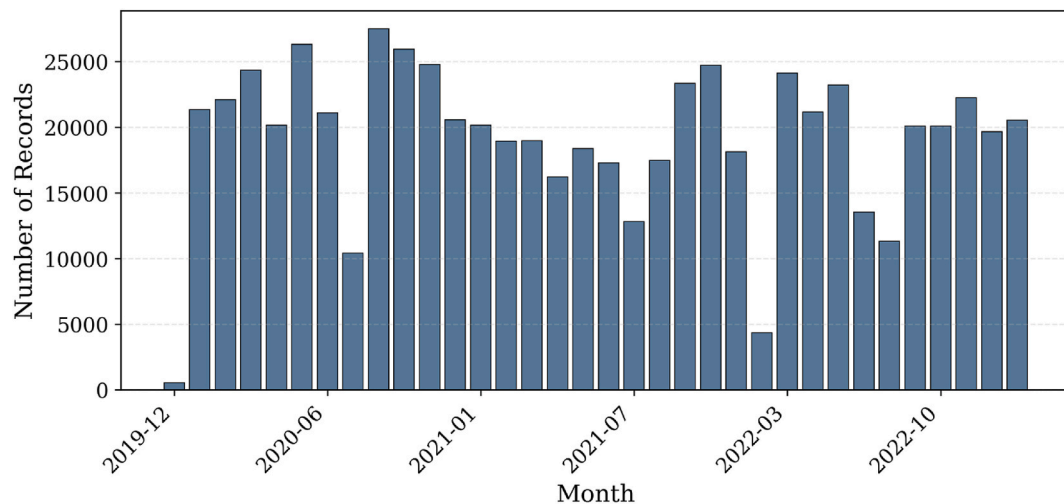


Fig. 2. Data availability timeline showing temporal coverage of the monitoring period (December 2019 to January 2023). Overall coverage was 83.9% (946 of 1128 days).

(1.9% of that grid) correspond to a median of four active intervals per sensor per active day. The dataset contains no zero-volume readings by construction; the smallest recorded value is the 1-litre meter resolution, and 32.5% of readings sit at this floor (48.4% at or below 2 L), reflecting frequent small, brief draw-offs rather than missing or heartbeat values. A missingness analysis by cluster and month confirmed that data gaps were generally distributed across the monitoring period without strong seasonal bias, though Cluster 5 exhibited notably lower coverage (28.6%) and Cluster 4 showed reduced availability (62.6%); these are addressed by the sensitivity analysis in Section 3.7.

2.4. Statistical analysis

Throughout this paper, end use denotes the fixture category at which water is drawn (shower, toilet, kitchen tap, washbasin, washing machine), and supply line denotes the hot or cold feed metered upstream of that fixture. An end-use breakdown is therefore an aggregation of the individual fixture meters into these five categories, and it is reported separately by supply line where the hot-cold split is informative. The analysis proceeds in the order shown in Fig. 1 and reported in Sections 3.1–3.10. Except for the data-quality diagnostics in Sections 3.1–3.2, descriptive statistics were computed for the residential analytical dataset and stratified by end use, supply line, residential cluster, dwelling unit and temporal period. (i) The end-use breakdown (Section 3.3) reports the total volume and percentage share of each of the five fixture categories. (ii) The supply-line breakdown (Section 3.4) reports the hot fraction overall and per end use, from which heating energy is computed as $E = \rho \cdot c_p \cdot V \cdot \Delta T$, assuming a cold water inlet temperature of 8°C, a hot water delivery temperature of 55°C ($\Delta T = 47$ K), $c_p = 4.186$ kJ/(kg·K), and a Swedish district heating emission factor of 47 g CO₂/kWh. (iii) Temporal profiles (Section 3.5) are computed at diurnal, weekly and monthly resolution, with monthly totals normalised by the number of active days. (iv) Heterogeneity (Section 3.6) is quantified using the coefficient of variation (CV) of daily consumption per dwelling unit and cluster, and the Gini coefficient across the 28 dwelling units; because units differ both in typology and in length of observation, the Gini coefficient is reported in three forms — on cumulative volume, on exposure-normalised mean daily volume (a unit's total divided by its own number of active days), and within the communal typology alone — so that structural and behavioural contributions to inequality can be distinguished. (v) Robustness checks (Section 3.7) recompute the headline statistics excluding the two low-coverage clusters, and compare the periods before and after the lifting of Swedish pandemic restrictions. (vi) Peak demand (Section 3.8) is characterised through the

peak hour factor, defined as the maximum of the mean diurnal profile divided by its mean ($PHF = Q_{\max, \text{hour}} / Q_{\text{mean, hour}}$); the daily peak-to-mean ratio, defined as the maximum single-day total divided by the mean daily total over all valid days ($R_{\text{peak}} = Q_{\max, \text{day}} / Q_{\text{mean, day}}$); and fixture-level peak factors, defined analogously on daily fixture totals. Because a maximum is by construction sensitive to a single extreme day, each factor is also reported on a 99th-percentile-day basis. (vii) Temporal dependence (Section 3.9) is quantified by the lag-1 and lag-7 autocorrelation of daily building totals. (viii) Finally, the shower analysis (Section 3.10) feeds the low-flow retrofit scenarios reported in Table 3, in which annual savings are obtained by scaling the observed annual shower volume by the assumed reduction and converting the hot-water share to energy and CO₂ with the constants above.

Because 10-min readings are strongly autocorrelated, and because observations are repeated across dates within clusters and fixtures, three measures were taken to avoid overstating significance. First, all group-comparison tests use daily totals rather than individual readings as the unit of analysis, and the sample size and number of groups are reported with every test statistic. Second, in addition to the Kruskal–Wallis test, which treats daily totals as independent, a Friedman test blocked by date is reported for the same comparisons; blocking by date removes day-to-day common variation (weather, occupancy, holidays) and treats the repeated measurement of each end use or cluster on the same day as a within-block observation, with Kendall's W as the accompanying effect size. Third, uncertainty in aggregate means is quantified with a moving-block bootstrap (block length 14 days, 2000 resamples), which preserves short-range serial dependence, and the effective sample size implied by the lag-1 autocorrelation, $n_{\text{eff}} = n(1 - r_1)/(1 + r_1)$, is reported alongside the nominal number of days. Non-parametric tests were used throughout, given the non-normal distribution of water consumption data: Kruskal–Wallis for multi-group comparisons across clusters and end uses, Friedman for the same comparisons under date blocking, and Mann–Whitney U for pairwise comparisons (e.g., morning vs. evening peaks). Effect sizes (ϵ^2 for Kruskal–Wallis, Kendall's W for Friedman,

Table 3

Estimated annual savings from a low-flow showerhead retrofit (hot fraction held at 64.4%; $\Delta T = 47$ K; 47 g CO₂/kWh; per-capita at ~33 residents).

Shower-volume reduction	Water saved (m ³ /yr)	Hot water saved (m ³ /yr)	Energy saved (kWh/yr)	CO ₂ saved (kg/yr)	CO ₂ saved (kg/person/yr)
20%	73	47	2576	121	3.7
30%	110	71	3864	182	5.5
40%	146	94	5152	242	7.3

rank-biserial r for Mann–Whitney) are reported alongside p -values so that significance is interpreted together with magnitude. Per-capita estimates were computed across the occupancy range of 30–35 residents. All analyses were performed using Python 3 with pandas and scipy.stats; the script that reproduces every numerical value reported below is included in the open data repository.

3. Results

3.1. Dataset overview and data quality

The cleaned meter dataset contains 652,315 valid consumption records spanning 946 valid days from December 2019 to January 2023. After excluding 16,416 records from the six non-residential ground-floor washroom sensors, 635,899 records from 208 sensors remain in the residential analytical dataset. Fig. 2 illustrates data availability over the monitoring period, with sporadic gaps and three larger periods of data loss, in mid-2020, over the turn of 2021/2022 and in September 2022. Overall temporal coverage, defined as valid days divided by calendar days, was $946/1128 = 83.9\%$; cluster-level coverage, computed on the same denominator, ranged from 28.6% (Cluster 5) to 83.9% (Cluster 9). At sensor level, 123,449 active sensor-days were observed, 62.1% of the sensor-days falling inside an operational window on a valid day, the balance being dominated by genuine days of non-use rather than by data loss (Section 2.3). The missingness heatmap (Fig. 3) shows that data gaps were generally distributed across the monitoring period without strong seasonal bias, supporting the validity of temporal analyses. Monthly consumption totals were normalised by the number of active days to account for variable data availability. The mean consumption per individual 10-min reading was 5.0 L (median 3.0 L, SD 9.3 L); Fig. 4 shows the strongly right-skewed distribution of consumption values typical of water use data, with 79.7% of readings at or below 5 L and 98.1% at or below 30 L.

3.2. Outlier analysis and threshold justification

The outlier threshold of 0.3 m^3 per 10-min reading was justified through hydraulic plausibility analysis. The maximum flow rate for residential fixtures ranges from 6 L/min (low-flow tap) to 12 L/min (high-flow shower), yielding a theoretical maximum 10-min consumption of 120 L for a single fixture. The 0.3 m^3 threshold (300 L per 10 min) corresponds to a sustained flow rate of 30 L/min, well above any single fixture capacity and conservative even for simultaneous multi-fixture use. Sensitivity analysis (Fig. 5) showed that whole-building meter consumption varied from 3145 m^3 at a 0.1 m^3 threshold to 3313 m^3 at

0.5 m^3 , i.e. -3.8% to $+1.3\%$ around the 3271 m^3 whole-building meter total obtained at the adopted 0.3 m^3 threshold, which removes 401 readings (0.06%). Above 0.2 m^3 the curve is nearly flat, changing the total by less than 1%, so the choice of threshold within the plausible hydraulic range does not materially affect any result. The 401 outlier readings were spread across all nine clusters (11 to 74 readings each) and 153 distinct sensors, of which 13 m shared facilities and account for 36 of the readings, so no single sensor or cluster accounted for a disproportionate share; this suggests random sensor errors rather than systematic malfunction at specific monitoring points.

3.3. Overall consumption and end-use breakdown

Residential water consumption over the monitoring period was 3109.891 m^3 , with a mean daily consumption of 3.29 m^3 (moving-block bootstrap 95% CI $3.10\text{--}3.49 \text{ m}^3/\text{day}$). The complete cleaned meter dataset contained a further 160.898 m^3 from two ground-floor washrooms used primarily for meeting and conference activities; this non-residential volume is reported separately and excluded from all results below. Of the residential total, 2916.264 m^3 (93.8%) is attributable to the nine residential clusters, while the social laundry studio (186.178 m^3) and cleaning room (7.449 m^3) together account for 193.627 m^3 (6.2%). Under the occupancy assumption of 30 to 35 residents, per-capita residential consumption ranges from 94 to 110 L/person/day (Fig. 6); propagating the bootstrap interval gives 89–100 L/person/day at 35 residents and 103–116 L/person/day at 30 residents. Residential shared spaces comprise 470.315 m^3 in cluster kitchens/social areas, 717.611 m^3 in shared cluster bathrooms and 7.449 m^3 in the cleaning room, totalling 1195.375 m^3 or 38.4% of residential consumption. The two separately metered private kitchens in one-room conventional flats are counted as private. Excluding these shared spaces, the private-fixture estimate is 58–67 L/person/day. If the residential social laundry studio is also classified as shared, the shared volume is 1381.553 m^3 (44.4%) and the private-fixture estimate is 52–61 L/person/day. The 110 L/person/day estimate at 30 residents remains below the Swedish national average of 140 L/person/day.

Fig. 7 shows the residential breakdown by end use. Showers accounted for the largest share at 948 m^3 (30.5%), followed by kitchen taps at 807 m^3 (25.9%), toilets at 740 m^3 (23.8%), washbasins at 364 m^3 (11.7%) and washing machines at 251 m^3 (8.1%). A Kruskal–Wallis test on daily end-use totals confirmed statistically significant differences across the five categories ($H = 2896.1$, $k = 5$ groups, $n = 4700$ end-use-days, $p < 0.001$), with a very large effect size ($\epsilon^2 = 0.62$). Blocking by date gave the same conclusion (Friedman $\chi^2 = 2873.8$, $df = 4$, 918 complete daily blocks, $p < 0.001$, Kendall's $W = 0.78$), confirming that

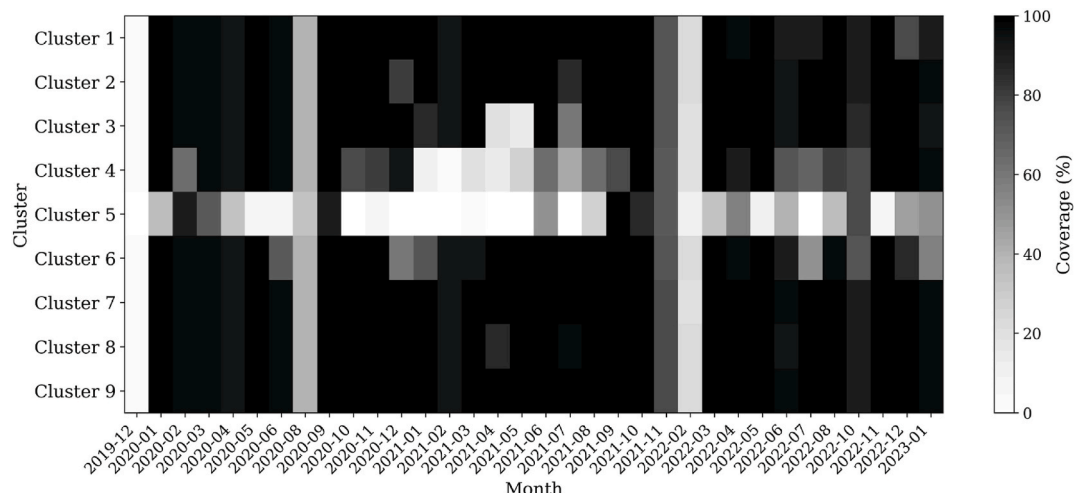


Fig. 3. Data availability heatmap by residential cluster and month, showing percentage of days with recorded data. Clusters 4 and 5 exhibit notably lower coverage.

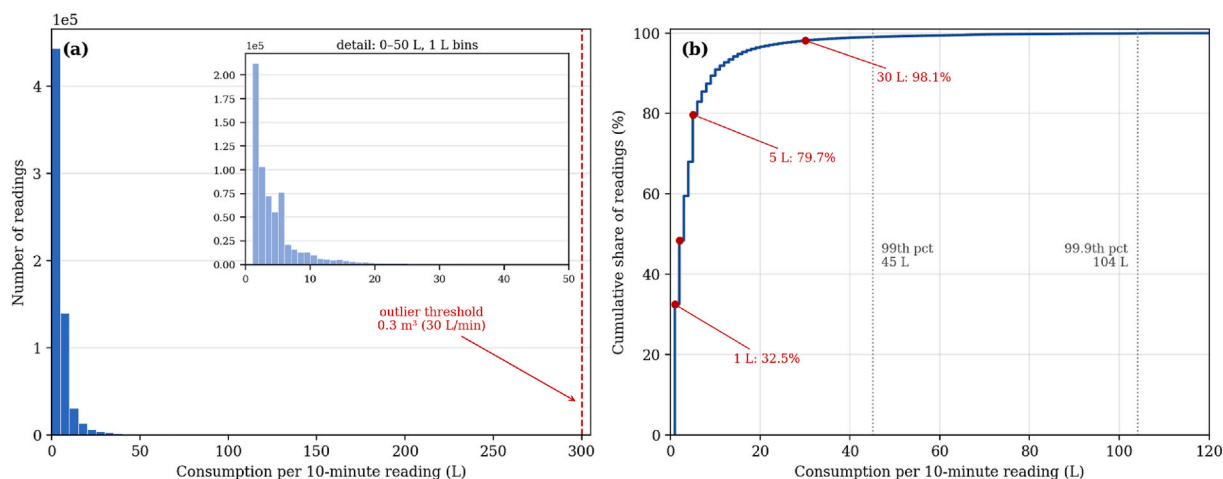


Fig. 4. Distribution of individual 10-min consumption readings. (a) Histogram over the full admissible range 0–300 L using 5 L bins, with an inset showing the 0–50 L range at 1 L resolution; the dashed line marks the 0.3 m³ outlier threshold. (b) Empirical cumulative distribution of the same readings, with the 99th and 99.9th percentiles indicated.

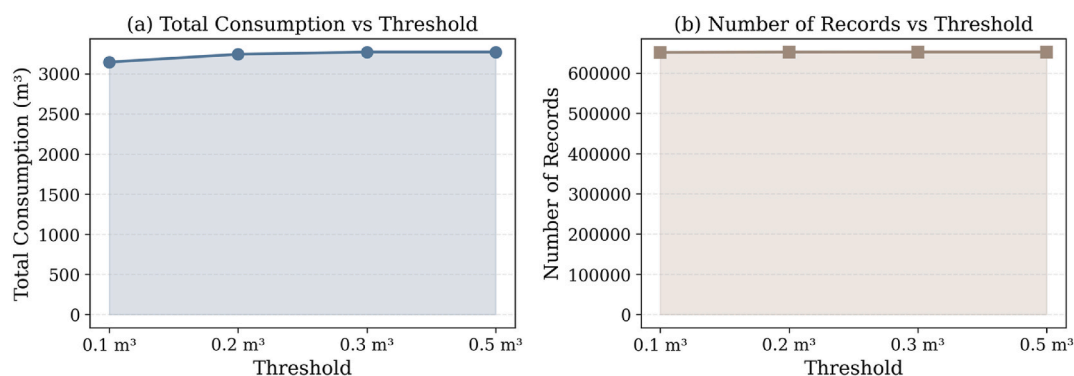


Fig. 5. Outlier threshold sensitivity analysis showing the effect of different thresholds on total consumption a) and number of records retained b).

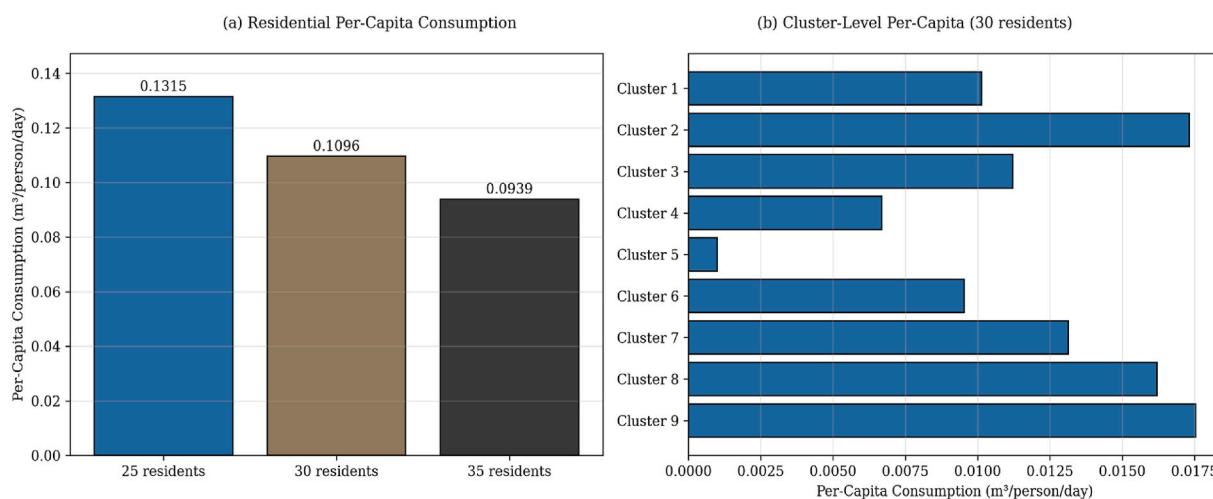


Fig. 6. Sensitivity analysis of residential per-capita daily water consumption under different occupancy assumptions, with the two non-residential meeting/conference washrooms excluded.

the ranking is stable within days.

3.4. Hot and cold water distribution and energy implications

Cold water constituted 1918 m³ (61.7%) and hot water 1192 m³

(38.3%) of residential consumption (Fig. 8). Showers exhibited the highest hot-water fraction (64.4% hot), followed by kitchen taps (49.1%) and washbasins (45.3%). Toilets were exclusively cold water, and washing machines used predominantly cold water (91.8% cold). These end-use-level hot fractions are compared with published values in

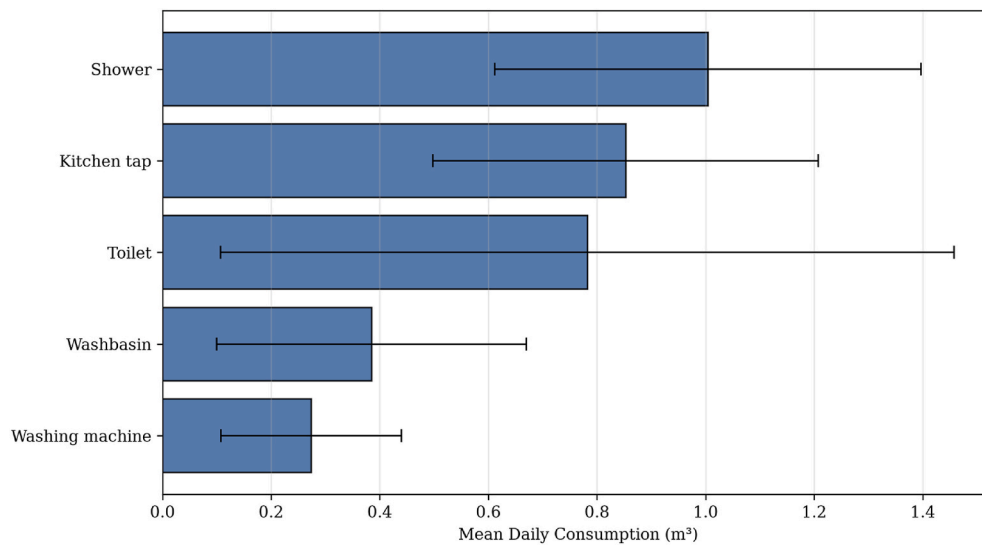


Fig. 7. Distribution of residential water consumption by end use. Differences were statistically significant (Kruskal–Wallis on daily end-use totals $H = 2896.1$, $k = 5$, $n = 4,700$, $p < 0.001$, $\epsilon^2 = 0.62$; Friedman blocked by date $\chi^2 = 2873.8$, $df = 4$, $N = 918$, $p < 0.001$, Kendall's $W = 0.78$).

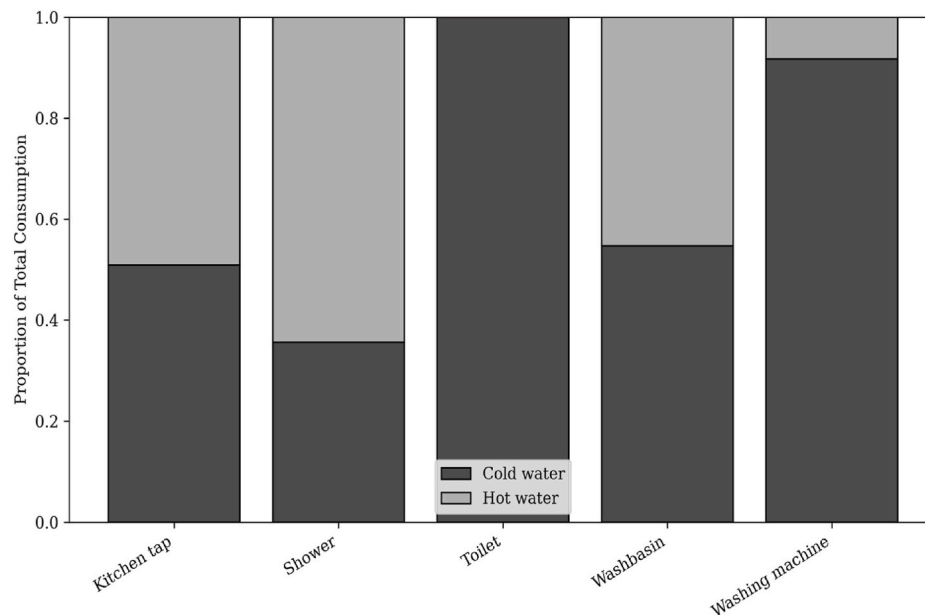


Fig. 8. Hot and cold residential water consumption by end use. Showers have the highest hot-water fraction (64.4%).

Section 4.2.

The energy demand for heating 1192 m³ of residential hot water (assuming $\Delta T = 47$ K) was estimated at 65,138 kWh over the monitoring period, or approximately 25,150 kWh per year. Using a Swedish district heating emission factor of 47 g CO₂/kWh, this corresponds to 1182 kg CO₂ per year. On the consistent 30–35-resident basis, hot-water heating requires approximately 719 to 838 kWh per person per year and 34 to 39 kg CO₂ per person per year. These estimates represent theoretical heating requirements based on temperature differential alone, excluding distribution, storage and heat-exchanger losses; actual delivered energy is likely 10–20% higher.

Because showers are both the largest end use and the most hot-water-intensive, they are the highest-leverage target for coupled water–energy savings. Table 3 and Fig. 9 quantify a low-flow/aerated showerhead retrofit under three shower-volume-reduction scenarios: a representative 30% reduction would save about 110 m³ of water and 3900 kWh of heating energy per year building-wide (≈ 180 kg CO₂/year).

3.5. Temporal patterns

The mean residential diurnal profile (Fig. 10) revealed a dual-peak structure. The highest hourly consumption occurred at 22:00 (mean 209.8 L/h), with secondary peaks at 19:00 (206.8 L/h), 18:00 (204.9 L/h) and 12:00 (195.0 L/h). The peak hour factor, the maximum of this mean diurnal profile divided by its mean of 137.0 L/h, was 1.53. A Mann–Whitney U test confirmed that consumption at 22:00 was significantly higher than at the morning peak at 10:00 (209.8 vs 183.5 L/h; $U = 528,022$, $n = 946$ days per group, $p < 0.001$), with a small effect size (rank-biserial $r = 0.18$). As shown in Section 3.6, the late-evening peak is primarily a signature of the communal clusters; conventional apartments peak earlier, around 19:00.

Weekly analysis (Fig. 11) showed Monday as the highest-consumption day (466 m³ cumulative), followed by Sunday and Thursday (463 m³ each), with Friday recording the lowest (414 m³); the weekday–weekend difference in daily totals was not statistically

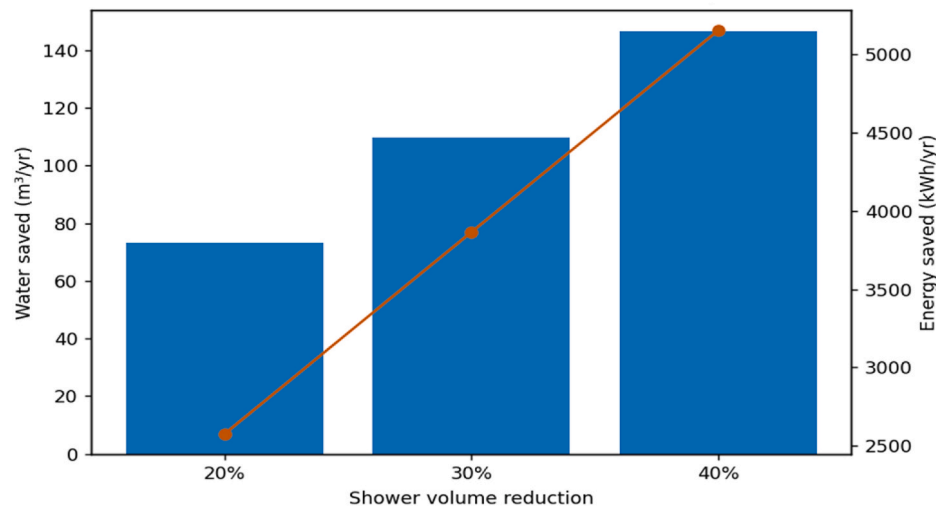


Fig. 9. Estimated annual water and heating-energy savings from a low-flow showerhead retrofit, by shower-volume reduction scenario.

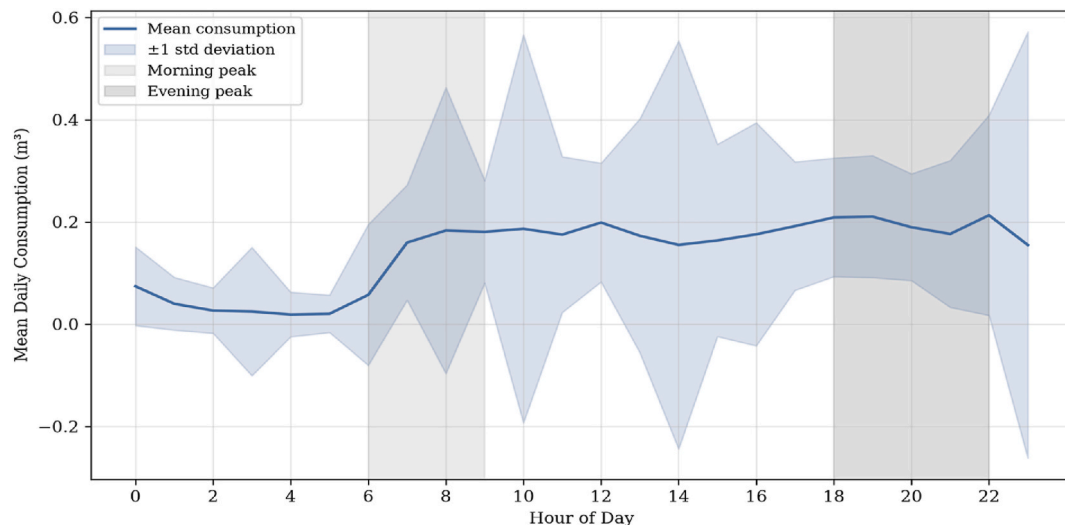


Fig. 10. Mean residential diurnal water-consumption profile. The 22:00 peak was significantly higher than the morning peak (Mann–Whitney U test, $p < 0.001$).

significant ($p = 0.12$). Monthly patterns (Fig. 12) revealed pronounced seasonal variation. March recorded the highest cumulative residential consumption (353 m^3), closely followed by October (339 m^3), while July showed a minimum of 107 m^3 , approximately 70% below the March maximum. This reflects summer vacancy rather than a change in per-resident behaviour. The pattern persisted after normalisation by active data days.

3.6. Intra-building heterogeneity and housing typology

Substantial variation in consumption was observed across residential clusters (Fig. 13). A Kruskal–Wallis test on daily cluster totals confirmed statistically significant differences across the nine clusters ($H = 2229.9$, $k = 9$ groups, $n = 7456$ cluster-days, $p < 0.001$), with a large effect size ($\epsilon^2 = 0.30$); the same comparison blocked by date, which restricts attention to the 281 days on which all nine clusters reported, gave the same conclusion (Friedman $\chi^2 = 1262.6$, $df = 8$, $p < 0.001$, Kendall's $W = 0.56$). Cluster 9 recorded the highest total consumption (498 m^3 , 17.1% of cluster-attributed volume), while Cluster 5 showed the lowest (28 m^3 , 1.0%). The coefficient of variation (CV) of daily consumption ranged from 0.26 (Cluster 7) to 2.77 (Cluster 4) across clusters, with a mean CV of 0.84 across individual dwelling units. The Gini coefficient of

cumulative dwelling-unit consumption was 0.52 (Fig. 14). It is computed over the 1986 m^3 that can be attributed to an individual dwelling unit, which is the cluster-attributed volume of 2916 m^3 less the 930 m^3 drawn in the shared kitchens and bathrooms of the communal clusters, since that volume carries no unit label. On this basis the five highest-consuming units, 18% of the 28 monitored units, account for 61% of unit-attributable volume (42% of cluster-attributed volume). This measure, however, mixes three distinct sources of variation — differences in behaviour, the structural difference between a 13 m^2 private room and a four-room flat, and unequal observation periods (323 to 945 active days per unit). Normalising each unit by its own number of active days reduces the Gini coefficient to 0.46, and computing it within the communal typology alone, where units are structurally comparable and exposure is similar, reduces it further to 0.21 (0.17 on the exposure-normalised measure). Inequality in this building is therefore predominantly structural rather than behavioural, and the headline value of 0.52 should be read as an upper bound; it is interpreted accordingly in Section 4.5.

Much of this heterogeneity is explained by housing typology (Fig. 15). Grouping clusters into communal (C1, C2, C8, C9) and conventional (C3–C7) reveals systematic differences (Table 4): communal clusters have a high within-cluster shared-space share and peak late

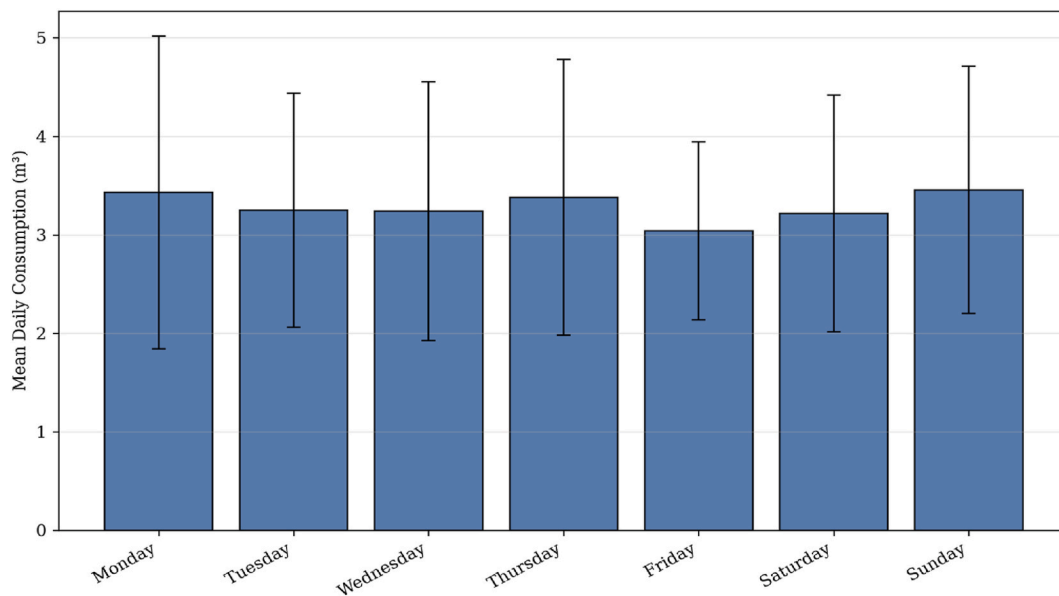


Fig. 11. Weekly water consumption patterns by day of week.

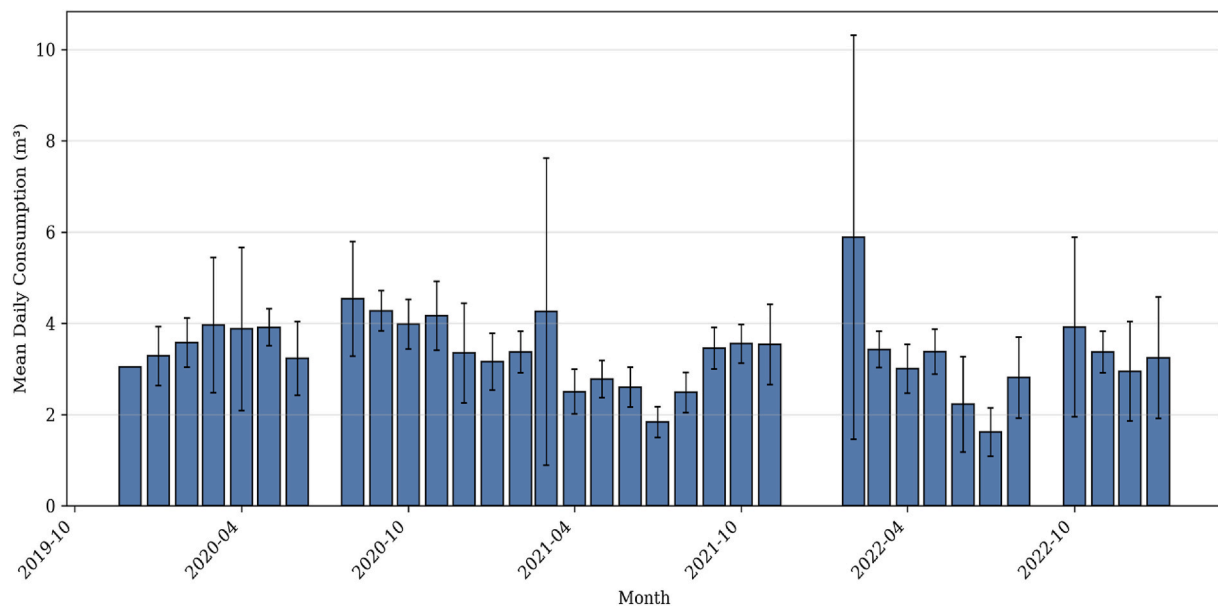


Fig. 12. Monthly water consumption patterns. The July minimum reflects summer vacation periods.

(22:00), with a higher hot-water fraction, whereas conventional apartments show a family-type profile with private washing machines, an earlier 19:00 peak and a toilet-dominated mix (Fig. 16). The two typologies together account for 2916 m³, or 93.8% of the 3110 m³ residential analytical total. The remaining residential volume is consumed in the social laundry studio (186.178 m³) and cleaning room (7.449 m³), which serve both typologies and cannot be assigned to either. The separate 160.898 m³ from the meeting/conference washrooms is outside the residential boundary. Table 4 therefore gives typology shares of both cluster-attributed and residential consumption. Within the cluster-attributed data, 53.5% of communal consumption is drawn in shared kitchens and bathrooms, versus 21.9% in conventional flats. A communal unit is one room housing roughly one person, whereas a conventional unit is a whole flat housing several; under the occupancy model of Section 2.1, communal per-capita use is approximately 83 L/person/day and conventional use approximately 96–156 L/person/day.

The comparison is qualitative because conventional occupancy is uncertain. Because much communal consumption is collective, hybrid metering and billing remains more appropriate than purely individual volumetric billing.

Fig. 17 presents boxplots of daily consumption per apartment, revealing substantial within-apartment variability as well as between-apartment differences.

3.7. Robustness: low-coverage clusters and the pandemic period

Because Clusters 4 and 5 had lower data coverage (62.6% and 28.6%), headline residential statistics were recomputed with both excluded. Results changed only marginally (total 2892 m³; shower share 31.4%; hot fraction 38.9%; apartment Gini essentially unchanged; 22:00 peak retained), confirming robustness; the clusters represent 7.5% of cluster-attributed volume and are retained with this note.

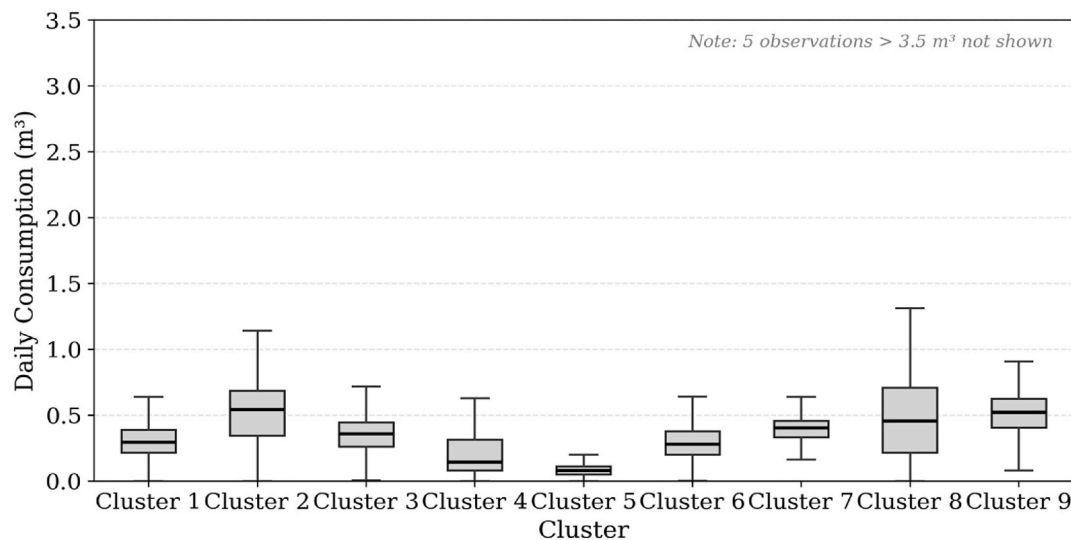


Fig. 13. Comparison of total water consumption across residential clusters. Differences were statistically significant (Kruskal–Wallis on daily cluster totals $H = 2229.9$, $k = 9$, $n = 7,456$, $p < 0.001$, $\epsilon^2 = 0.30$).

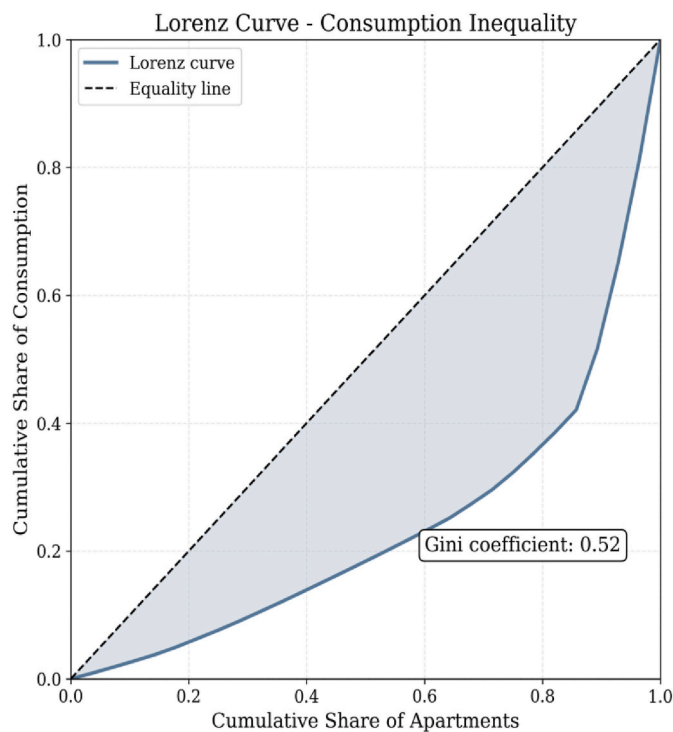


Fig. 14. Lorenz curve of cumulative water consumption across apartments. The Gini coefficient of 0.52 indicates moderate inequality in water use distribution.

The monitoring window overlaps the COVID-19 pandemic, with only about five weeks preceding it, so a true pre/post comparison is not possible. Comparing the restriction period with the period after restrictions were lifted on 9 February 2022, residential consumption normalised per active apartment was modestly lower afterwards (163 vs 140 L/apartment/day), but the diurnal shape was essentially unchanged ($r = 0.96$; Fig. 18). Linear regression of monthly residential consumption per active dwelling unit over the 34 months with data showed no significant trend ($p = 0.49$), supporting the discussion of a possible novelty effect in Section 4.6.

3.8. Peak demand analysis

Peak demand factors provide critical parameters for infrastructure sizing (Fig. 19). The residential daily peak-to-mean ratio was $R_{\text{peak}} = 14.48/3.287 = 4.40$. Because a maximum is determined by a single day, the ratio on the 99th-percentile day is also reported: 2.49, the more robust design value. The peak hour factor was $\text{PHF} = 209.8/137.0 = 1.53$. Among end uses, washbasins and toilets had the highest daily peak-to-mean ratios (13.4 and 13.1, falling to 2.7 and 2.8 on the 99th-percentile-day definition). Showers, the largest end use, were least peaky (2.9, or 1.9 on the robust definition), favourable for hot-water system sizing.

3.9. Autocorrelation and temporal persistence

Autocorrelation analysis of residential daily totals revealed moderate persistence. Over the 936 valid lag-1 pairs, $r_1 = 0.65$; over 911 lag-7 pairs, $r_7 = 0.31$. The lag-1 value indicates that approximately 43% of daily variance is associated with the previous day and implies an effective sample size of approximately 199 independent days out of 946. The moving-block bootstrap interval for mean daily consumption was 3.10–3.49 m³/day around a mean of 3.29 m³/day, 0.38 m³/day wide and 2.26 times the 0.17 m³/day ordinary-bootstrap interval. This is close to the factor $\sqrt{(946/199)} = 2.18$ implied by the effective sample size and supports sustained rather than snapshot monitoring.

3.10. Shower analysis

A dedicated analysis of shower events was performed to characterize this dominant and most energy-intensive end use. Fig. 20a presents the distribution of individual shower readings and Fig. 20b their timing. Fig. 21 places this alongside the normalised residential diurnal pattern of the other end uses. Showering is the largest contributor to the 22:00 residential peak, at 33.7% of the volume drawn in that hour, ahead of toilets (26.1%) and kitchen taps (23.0%), and its profile is most sharply concentrated in the late evening.

4. Discussion

4.1. Per-capita consumption in context

The per-capita consumption reported in Section 3.3, 94 to 110 L/person/day (residential analytical, depending on assumed occupancy at

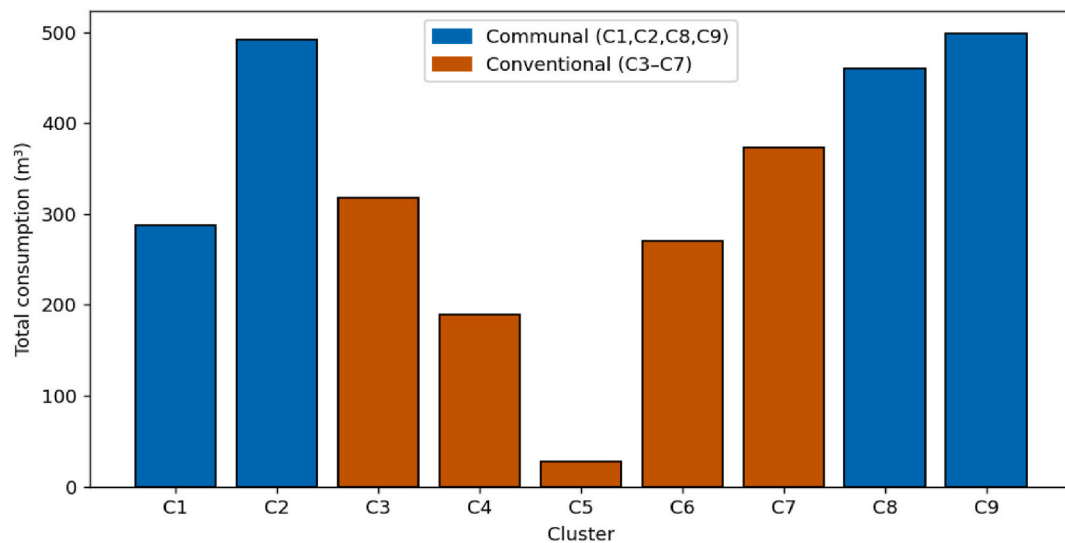


Fig. 15. Cluster consumption coloured by housing typology (communal vs conventional).

Table 4

Communal versus conventional clusters. Percentages of cluster-attributed volume use 2916 m³ as denominator; shares of the 3109.891 m³ residential analytical total are given separately. The per-unit row uses the complete group volume and the common 946-day observation period.

Metric	Communal (C1, C2, C8, C9)	Conventional (C3–C7)
Dwelling units (n)	23	5
Sensors	159	38
Total consumption (share of the 2916 m ³ cluster-attributed volume)	1737 m ³ (59.6%)	1179 m ³ (40.4%)
Share of the 3109.891 m ³ residential total	55.9%	37.9%
Dominant end use (share of group volume)	Shower (37.0%)	Toilet (30.2%)
Hot-water fraction (hot ÷ group total)	44.5%	33.1%
Shared-space share within group	53.5%	21.9%
Diurnal peak hour	22:00	19:00
Period-normalised use per monitored unit (U _{period})	80 L/day (private room)	249 L/day (whole flat)

Table 4 reports one period-normalised per-unit measure with a consistent accounting boundary: $U_{\text{period}} = V_{\text{group}} / (946 \times N)$, where V_{group} is the complete typology volume, including its cluster-level shared spaces, and N is the number of monitored dwelling units. The resulting values are 80 L/unit/day for the 23 communal rooms and 249 L/unit/day for the five conventional flats. The same volume boundary and observation period are thus used for both typologies. These rates remain structurally different—a communal unit is a private room, whereas a conventional unit is a complete flat—and the occupancy-based comparison above is therefore more interpretable.

30–35 residents), places the HSB Living Lab below the Swedish national average of 140 L/person/day and in the lower range internationally. The REUWS study in the USA (DeOreo et al., 2016) reported 300 L/person/day; Willis et al. (2011) found 158 L/person/day in Australia; Hussien et al. (2016) reported 145 L/person/day in the UK; and Domene and Sauri (2006) found 216 L/person/day in Spain. The recent worldwide review of residential end uses (Mazzoni et al., 2023) situates such figures within a wide global distribution shaped by climate, pricing, dwelling type and metering method, and the large multi-city smart-meter analyses of Naseri et al. (2025, 2026), covering tens of thousands of single-family households across 39 US cities, confirm that shower and toilet use are the principal discriminators between high- and low-consuming populations — the same two end uses that dominate here. The present study's 30-resident estimate of 110 L/person/day (residential analytical, 30 residents) is notably lower, likely reflecting

the student demographic, the shared housing model, and the Northern European context.

Several factors plausibly contribute to the relatively low consumption. They are highlighted because they are the characteristics that distinguish this sample from the literature comparators, rather than because they are uniquely causal, and each can now be weighed against a specific body of evidence. (1) The demographic composition of predominantly young students is associated with distinctive rather than uniformly lower use: Otrubina et al. (2025), monitoring showers in university student housing, found longer and more variable shower events than in single-family residences, so the low aggregate observed here is unlikely to be driven by shower behaviour and is more consistent with the small private dwellings and with the absence of outdoor, garden and large-appliance uses that inflate single-family comparators. (2) The shared housing model may promote conservative use through social accountability and shared infrastructure; the counterpart evidence is that collective metering weakens the individual price signal and is associated with higher use, with Carrillo et al. (2024) estimating a reduction of about 20% when individual metering replaces collective metering. The direction of this effect is therefore ambiguous, and the observed low level is achieved despite, rather than because of, the collective billing arrangement. (3) Awareness of living in a monitored facility (Hawthorne effect) is discussed critically in Section 4.6; the absence of a decaying trend over the three-year window argues against a large time-varying artefact, although a stable level shift cannot be excluded, and the multi-year persistence of feedback-induced savings reported by Cominola et al. (2021) indicates that a monitoring-related effect need not decay over the observation window. (4) The small private dwellings in the communal clusters (13 m² rooms) limit water-intensive activities, which is consistent with the decomposition of fixture efficiency and behaviour in Naseri et al. (2026), where dwelling and appliance characteristics account for a substantial part of between-household differences. Other established determinants — water price, climate, household size and cultural habits (Arbués et al., 2003; Fielding et al., 2012) — may also contribute but cannot be resolved with the anonymized data, so these figures should be read as characteristic of this housing context rather than as isolating any single cause.

4.2. End-use composition and the hot-cold split

The residential end-use distribution reported in Section 3.3 (showers 30.5%, kitchen taps 25.9%, toilets 23.8%, washbasins 11.7%, washing

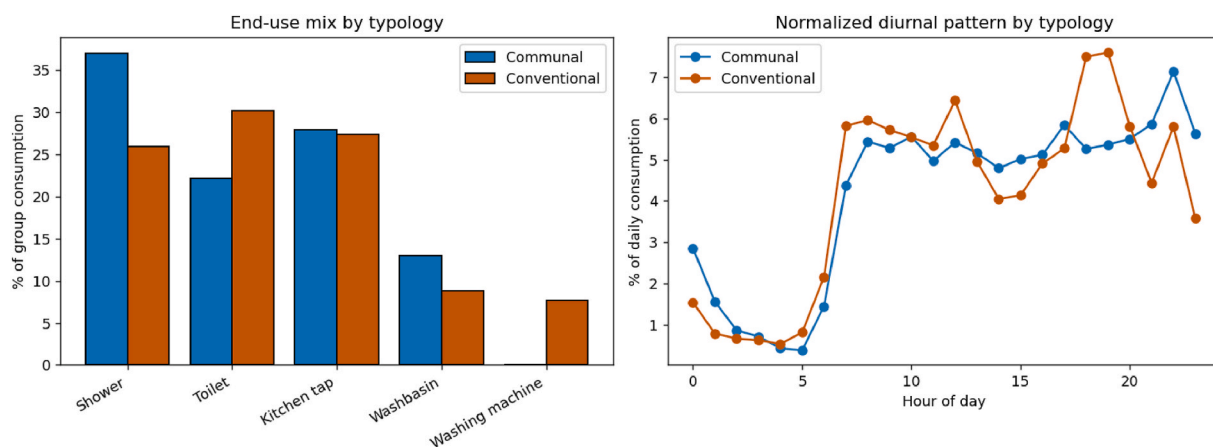


Fig. 16. End-use mix (left) and normalised diurnal pattern (right) for communal versus conventional clusters.

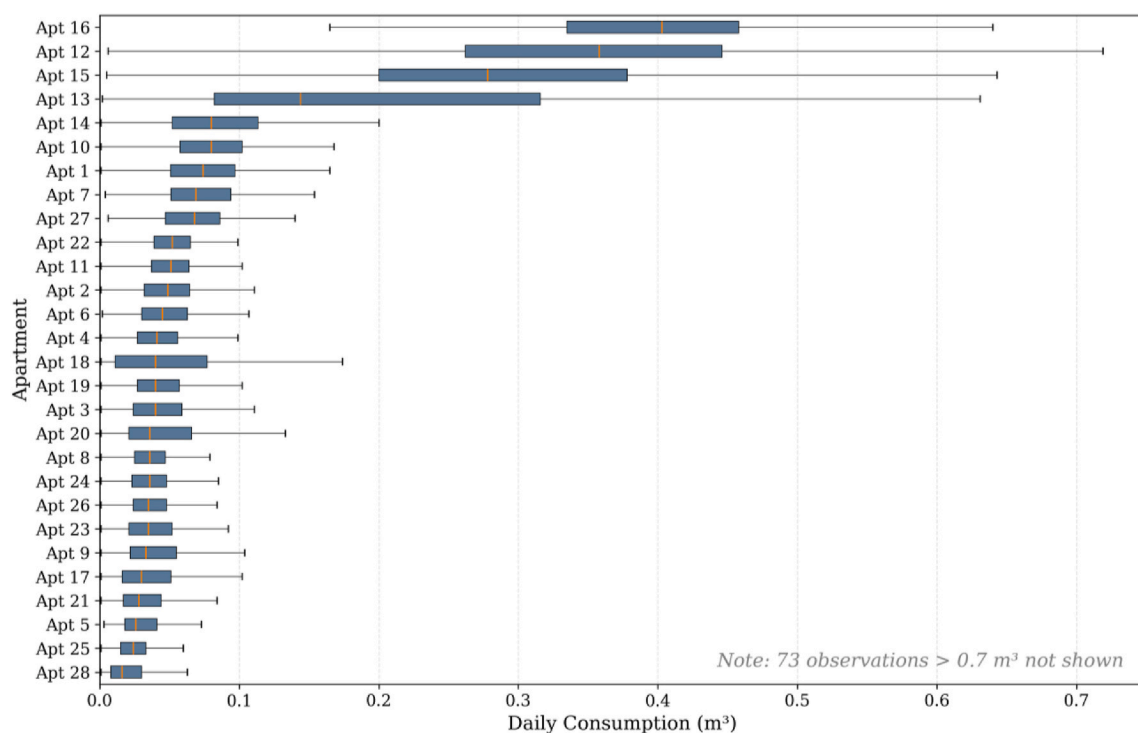


Fig. 17. Boxplots of daily water consumption by apartment, sorted by median, showing both within- and between-apartment variability.

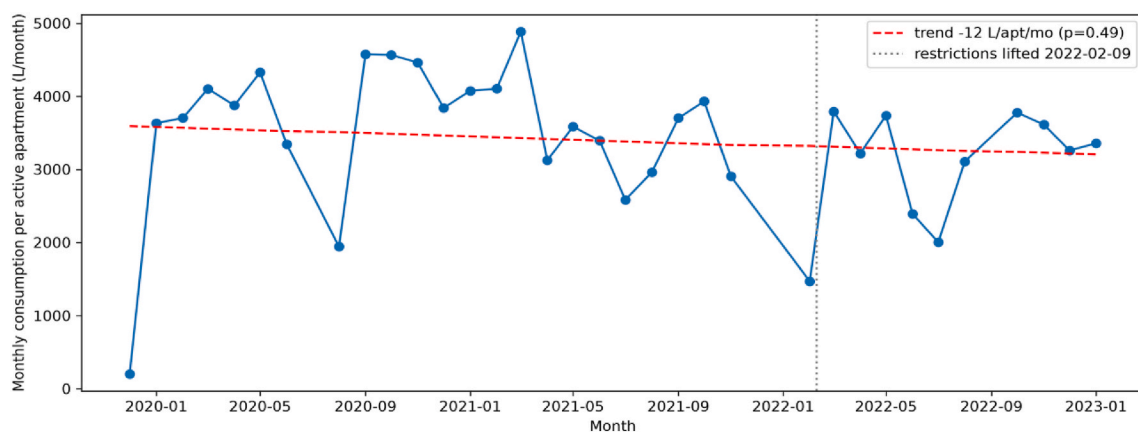


Fig. 18. Monthly residential consumption per active apartment, with linear trend and the date Swedish restrictions were lifted.

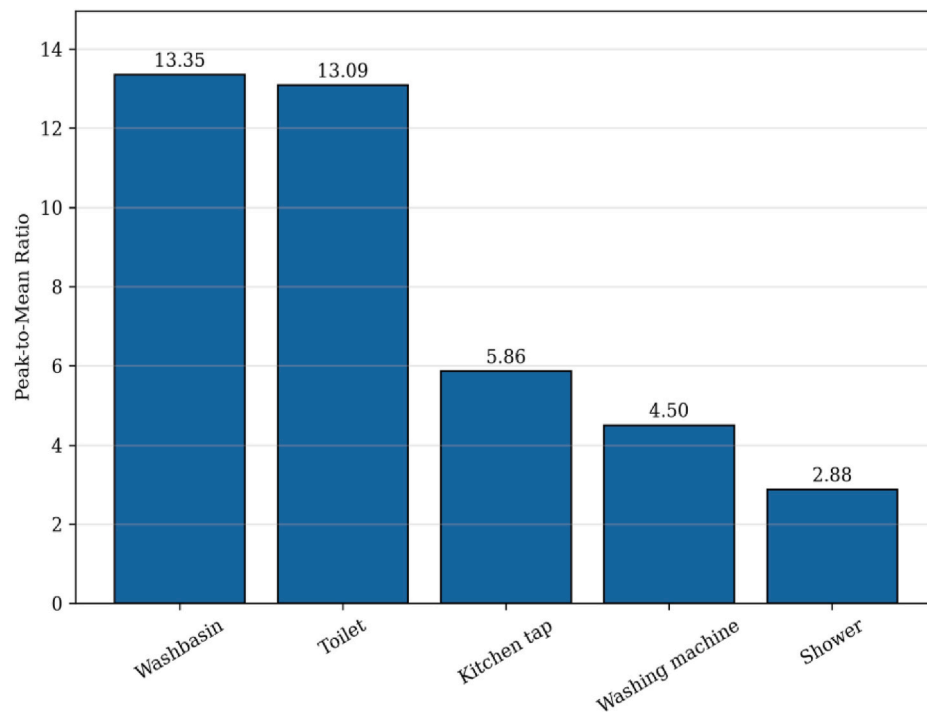


Fig. 19. Peak demand analysis showing daily peak-to-mean ratios by end use.

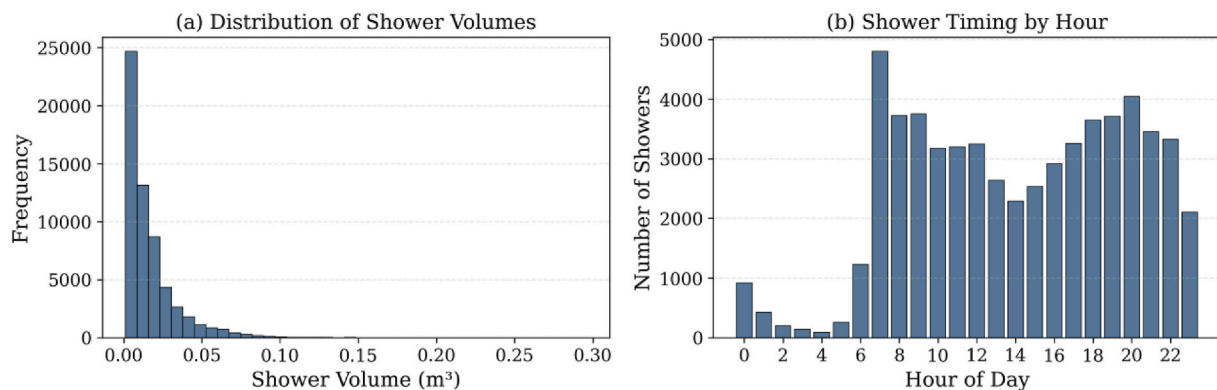


Fig. 20. Distribution of shower water consumption events (a) and shower timing by hour of day (b).

machines 8.1%) is broadly consistent with published REUWS and Australian distributions, though the HSB Living Lab shows a markedly higher shower fraction (DeOreo et al., 2016; Vieira et al., 2017). Showering is proportionally more prominent where clothes washing is partly displaced to shared facilities and outdoor uses are absent, while the student demographic showers longer and more variably than single-family occupants (Otrubina et al., 2025).

The separately metered supply lines allow the hot fraction to be resolved for each end use, which is rarely available in end-use studies and is the level at which water and energy conservation measures actually interact. Showers were the most hot-water-intensive end use at 64.4% hot, followed by kitchen taps at 49.1%, washbasins at 45.3% and washing machines at 8.2%, with toilets exclusively cold. These values sit within the range synthesised in the worldwide review of residential hot-water consumption (Mazzoni et al., 2026) and are close to the shower hot-water fractions of roughly 60–75% reported for North American and Southern European housing (DeOreo et al., 2016; Papakostas et al., 1995). The kitchen-tap value is at the upper end of published figures, which is consistent with a cold climate and a low mains temperature: the lower the incoming cold-water temperature, the larger the hot-water

share required to reach a given delivery temperature. The residential hot fraction of 38.3% is likewise close to the value of about 40% reported by REUWS, indicating that the aggregate hot-cold balance transfers reasonably well across these contexts even where the end-use mix does not. The practical implication is that the ranking of end uses by coupled water–energy intensity, rather than by volume alone, is the transferable output of fixture-level hot and cold metering.

4.3. Energy–water nexus and intervention potential

The finding reported in Section 3.4, that hot water constitutes 38.3% of total consumption, has significant energy implications. The estimated annual energy demand of 25,150 kWh for hot water heating corresponds to approximately 719 to 838 kWh per person per year (30–35 residents), a non-trivial component of household energy use, consistent with the patterns synthesised in the worldwide review of residential hot-water use (Mazzoni et al., 2026) and broadly comparable to the hot-water energy figures reported by (Papakostas et al., 1995). Critically, 64.4% of shower water is hot, meaning that shower-specific interventions (low-flow showerheads, temperature limiters, real-time

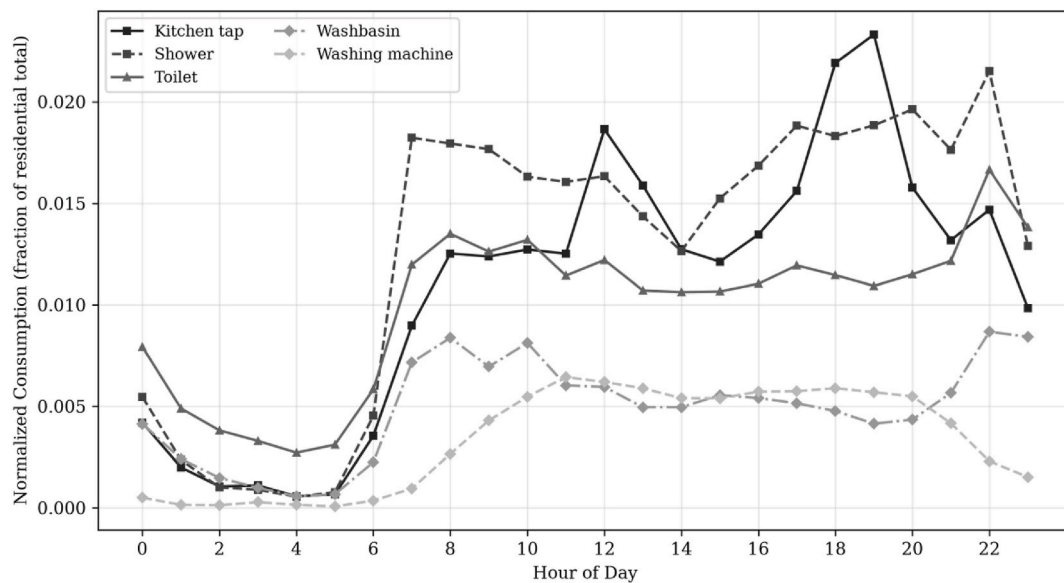


Fig. 21. Normalised residential diurnal pattern by end use across the full monitoring period.

feedback) could simultaneously address both water and energy conservation. As quantified in Table 3, reducing shower volume by 20% would save approximately 2600 kWh per year building-wide, rising to about 3900 kWh at a 30% reduction, illustrating the general cleaner-production principle that disaggregated monitoring allows interventions to be targeted where the coupled water-energy intensity is highest rather than applied uniformly. It should be noted that these energy estimates represent theoretical heating requirements based on temperature differential alone, excluding distribution losses, storage standby losses, and heat exchanger inefficiencies; actual delivered energy is likely 10–20% higher than the theoretical values reported here.

4.4. Temporal patterns and infrastructure implications

The diurnal pattern with a peak at 22:00 differs notably from typical residential patterns reported in the literature, which generally show a dominant morning peak between 07:00 and 09:00 (Stewart et al., 2010). As shown in Section 3.6, this evening-dominant pattern is primarily a signature of the communal (student) clusters, which peak at 22:00, whereas the conventional apartments peak earlier (19:00), closer to mainstream housing; the building-level 22:00 peak therefore arises from late-evening showering in the communal clusters superimposed on the conventional early-evening peak. The daily peak-to-mean ratio of 4.40 and peak hour factor of 1.53 provide design parameters for infrastructure engineers, though the corresponding 99th-percentile-day factor of 2.49 (Section 3.8) is the more robust basis for sizing, since the maximum is set by a single day. The pronounced July minimum (68% reduction from the March maximum) provides a clear vacation signature valuable for demand forecasting and infrastructure maintenance scheduling (Arbués et al., 2010). The persistence structure quantified in Section 3.9 is directly relevant here: with a lag-1 autocorrelation of 0.65 and an effective sample size of roughly 199 independent days in three years, short monitoring campaigns of a few weeks carry far less independent information than their nominal record length suggests, which is a practical argument for sustained rather than snapshot metering.

4.5. Intra-building heterogeneity and transferability

The Gini coefficient of 0.52 on cumulative consumption indicates moderate inequality in water use distribution, but Section 3.6 shows that most of it is structural rather than behavioural: normalising for unequal observation periods lowers it to 0.46, and restricting the calculation to

the structurally comparable communal units lowers it to 0.21. The headline value should therefore not be read as evidence of large behavioural differences between residents, and it is reported here as an upper bound. What remains after this decomposition is nonetheless policy-relevant: average consumption figures mask substantial unit-to-unit variation ($CV = 0.84$), and the statistically significant differences across clusters are substantially explained by housing typology (Section 3.6), with communal clusters and conventional apartments differing systematically in end-use mix, hot fraction, shared-space share and peak timing. This reframes the question of generalisability. Findings tied to the communal model — the high 38.4% residential shared-space share, the very low per-room volumes, and the 22:00 peak — are specific to shared student housing and should be transferred only to comparable settings. Findings observed across both typologies — the dominance of showers in hot-water-related energy, the right-skewed reading distribution, the multi-year stability of seasonal patterns, and the peak-demand factors for the conventional flats — are more readily transferable to mainstream housing. The presence of conventional one-to four-room apartments in the same building, climate and metering system makes this distinction empirically grounded rather than assumed. Where targeting is warranted, the evidence from metering interventions suggests that it works best when tied to a specific, diagnosable end use rather than to aggregate consumption (Rupiper et al., 2024).

4.6. The living lab as a research environment

The Habitation Lab offers high internal validity, every fixture is metered separately for hot and cold water over several years in genuinely occupied dwellings, at some cost to external validity, since residents are partly self-selected, aware of monitoring, and skew young. Two pieces of evidence temper the usual concerns. First, the within-building conventional apartments behave much like mainstream housing, providing an internal reference point. Second, regarding the Hawthorne effect, consumption showed no statistically significant trend over the three-year monitoring window (Section 3.7); were a strong novelty effect present and decaying, an upward drift would be expected as awareness faded, which is not observed. While a stable level shift cannot be excluded, this argues against a large, time-varying monitoring artefact persisting over three years. The pandemic overlap is a genuine caveat given the absence of a real pre-pandemic baseline, but the near-identical diurnal shape before and after restrictions were lifted ($r = 0.96$) indicates that the time-of-day patterns are not pandemic

artefacts. Finally, the Nordic context matters for interpretation: Swedish multi-family housing is almost universally served by district heating, and utilities including hot water are typically included in rent rather than individually billed, weakening the price signal that shapes consumption in many international comparators; combined with generally water-abundant conditions and local bathing and laundry norms, this context helps explain both the energy framing and the moderate overall volumes.

5. Study findings and limitations

The principal findings, each supported by statistical analysis, are: (1) residential per-capita consumption of 94 to 110 L/person/day (30–35 residents) is below the Swedish average of 140 L/person/day; (2) hot water constitutes 38.3% of residential consumption, corresponding to approximately 25,150 kWh and 1182 kg CO₂ per year, with showers (64.4% hot) the highest-leverage target; (3) the 22:00 peak is significantly higher than the morning peak ($p < 0.001$), with a peak hour factor of 1.53 and daily peak-to-mean ratio of 4.40 (2.49 on a 99th-percentile-day basis); and (4) large cluster differences are largely structured by housing typology, while the dwelling-unit Gini coefficient falls from 0.52 on cumulative volume to 0.21 within structurally comparable communal units.

Several limitations qualify these findings. First, data coverage was 83.9% at the level of valid days, and two conventional clusters fell below 65%; the sensitivity analysis in Section 3.7 shows that the headline results are robust to their exclusion. Second, because logging is event-triggered, a day on which an individual sensor records nothing cannot be distinguished from non-use with certainty at that sensor; the classification rule of Section 2.3 resolves this at building level but not sensor by sensor. Third, occupancy is estimated rather than metered, so per-capita figures are presented as ranges over 30–35 residents; per-capita estimation itself remains feasible, and the binding limitation is the attribution of shared-space consumption to individual residents. Fourth, the 1-litre meter resolution combined with 10-min aggregation smooths short-duration events and prevents disaggregation of individual activities within the same fixture. Fifth, the Gini coefficient and other inequality measures are computed across dwelling units that differ in size, typology and length of observation, so they characterize the building as configured rather than isolating behavioural variation; the decomposition in Section 3.6 is offered for this reason, and the headline value should be treated as an upper bound. Sixth, potential meter drift over the three-year period was not independently verified. Seventh, the monitoring window overlaps the COVID-19 pandemic with a negligible pre-pandemic baseline. Eighth, the partly student demographic limits direct generalisation of the communal-cluster results, mitigated but not eliminated by the conventional apartments in the same building. Ninth, the six ground-floor washroom sensors were excluded because those rooms principally serve meeting and conference activity; because individual users were not observed, incidental resident use of these washrooms cannot be separated from non-residential use. Their 160.898 m³ is therefore reported transparently outside the residential analytical boundary.

6. Conclusions

Sustained, fixture-level monitoring in a building that combines communal and conventional housing demonstrates how disaggregated water data can support cleaner, more resource-efficient residential systems. By resolving where consumption and its embedded heating energy are concentrated, showers, and the communal clusters, the data turn descriptive monitoring into actionable targeting: a single low-flow shower measure is estimated to cut roughly 110 m³ of water and 3900 kWh of heating energy per year, and the within-building typology comparison shows which conservation and infrastructure lessons transfer to mainstream housing and which are specific to shared student

living. For practitioners, the results argue for prioritising hot-water-intensive end uses, for hybrid metering and billing in shared housing, and for using context-appropriate peak-demand factors in design. For researchers, the dataset, over three years of fixture-level hot and cold measurements at 10-min resolution across 28 dwelling units and two housing typologies, openly available with the full reproduction script, is a rare resource for benchmarking, demand modelling and intervention testing. Future research should integrate occupancy data to improve per-capita estimates, implement real-time feedback systems to test the modelled shower savings in situ, and extend the typology comparison to additional building types.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the author used a generative AI assistant to enhance grammar, language and clarity of the text and to assist with data-analysis scripting and figure generation under the author's direction. After using this tool the author reviewed and edited the content as needed and takes full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The anonymized dataset, data dictionary, and analysis scripts underlying this study are openly available on Zenodo at <https://doi.org/10.5281/zenodo.18971106>, licensed under Creative Commons Attribution 4.0 International (CC BY 4.0).

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