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Patterns tell human stories: towards connecting residential water use to occupant behavior in a permanent supportive housing context

Hassaan Khan and Ashlynn S Stillwell*

Civil and Environmental Engineering, Grainger College of Engineering, University of Illinois Urbana-Champaign, Urbana, IL, United States of America

* Author to whom any correspondence should be addressed.

E-mail: ashlynn@illinois.edu

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Abstract

The quantification of residential water end uses is an important component of improving the sustainability of urban water infrastructure. Disaggregation and classification methods based on statistical learning are used in research and practice to extract meaningful insights from smart water meter data. These insights can also reflect individual behaviors within the built environment, enabling end-user activity detection from water consumption patterns. In this study, we present an initial framework for classifying residential water end uses and assisting with discerning between perceived typical and atypical water-use behavior in a permanent supportive housing context. Classification schemes, based on fine-resolution temporal flow data, incorporated baseline activity to inform what typical water use was for individuals while also considering general trends in specific end uses such as showers, toilet flushes, and leaks. We found that while atypical activity based on end-use duration and frequency might fall outside the normally-distributed expected value for a period of interest, it need not be the case for all atypical activity. Defining atypical activity based on prescriptive guidelines might not align with normative behavior for an occupant transitioning into housing. Additionally, exogenous variables can affect occupant behavior regarding water end uses and this impact should be accounted for in analytical frameworks. Our findings can specifically inform supportive services provided by stakeholders responsible for the well-being of individuals in their care via non-intrusive, privacy-respecting insights on occupant behavior.

1. Introduction

Understanding the 'how, when, and why' of people using water in residential settings is foundational to improving water demand forecasting, supporting conservation policies, and managing utility infrastructure more efficiently. Historically, residential water consumption was recorded at coarse intervals (monthly or quarterly) via manual meter readings [1]. While useful for billing, these readings offered little to no insight into the temporal patterns or causative behavioral underpinnings of water use. The use of fine-resolution smart water meters [2] has pushed towards digitalized infrastructure ('smart infrastructure') that enables near-continuous data collection, often at intervals ranging from one second to 5 min. Demand-side management solutions that support broad water sustainability are best developed from the bottom-up by incorporating household insights, rather than relying solely on top-down, one-size-fits-all solutions [3].

Disaggregating water-use events is essentially a 'blind source' separation task [4]; one attempts to decompose a complex signal (aggregate flow) into its constituent sources (e.g. toilet, faucet, shower) without direct information from those sources. Fine-resolution data (e.g. sub-minute intervals) dramatically improve the ability to disaggregate end uses and detect anomalies, yet pose substantial challenges in terms of data storage, processing, and privacy [5, 6]. One central tradeoff in smart water meter design is the balance between resolution and use case feasibility; experimental work has demonstrated that temporal resolutions of 1 to 5 s yield the highest classification accuracy for common residential end uses [7]. Certain end uses, particularly toilets and showers, have distinctive enough signatures to be reliably identified, whereas shorter, overlapping uses (concurrent events) such as faucets and leaks are harder to classify at coarser resolutions [4, 5].

In this study, we analyze residential water end uses from water consumption time series data measured by a custom ally® water meter. We disaggregated the water-use time series into discrete events and then classified into six distinct indoor end uses (shower, toilet, faucet, dishwasher, refrigerator faucet, washing machine) with all consumptive use attributed to indoor use. Similar to Mazzoni *et al* [8], we calculated consumption metrics to quantify the composition of residential water use. These end uses were then analyzed in relationship to human behaviors to create an initial framework for detecting 'atypical' activities. This framework can extend to provide useful knowledge for assistive services in a permanent supportive housing (PSH) context. Through this work, we answer the following research questions:

1. What aspects of water end uses can be used to ascertain behavioral information about the individuals performing those activities? Are statistical measures (such as dispersion) a good way to discern 'typical' and 'atypical' activity?
2. What, if any, is the effect of exogenous environmental variables such as outdoor air temperature on residents' specific end uses? How much of the variability in water consumption from a specific end use can be explained by some external variable?
3. What is normative behavior for individuals moving or acclimating to PSH?

We use measures of dispersion, causal inference, and primary sources (thorough semi-structured interviews) to answer these questions. Our findings can support further environmental and social sustainability outcomes through connecting residential water use and efficiency to occupant behavior and functioning.

2. Background

An 'end use' is a discrete water-consuming event initiated by a user or a fixture/appliance; real-world water consumption is not always so cleanly partitioned. Events can overlap (e.g. a faucet is left running while the dishwasher is operating), occur in rapid succession (e.g. back-to-back toilet flushes), or present similar flow signatures (e.g. a short shower might resemble a faucet use in aggregate data). These ambiguities present major classification challenges, especially when using non-intrusive sensing methods, where only total household flow is captured rather than per-fixture sub-metering. Additionally, water usage events vary significantly by household, context, and even season [8]. For example, outdoor irrigation is common in suburban areas but rare in high-density urban housing or supportive housing contexts. Similarly, the duration and frequency of shower events might differ dramatically based on cultural norms, health conditions, or housing design (e.g. shared vs. private bathrooms) [9–11]. The Residential End Uses of Water Study Update—Version 2 (REU2016), the follow-on study of the original 1999 study [12], provides detailed insights into how water is used in single-family homes across North America. The study analyzed data from approximately 23 749 homes across 23 diverse locations in the United States and Canada, offering a broad perspective on residential water consumption patterns [13] and found the average indoor water use to be 138 gallons per household per day with toilets being the largest indoor water end use, followed by faucets, showers, clothes washers, leaks, bathtubs, and dishwashers. REU2016 also highlighted a 22% decrease in average annual indoor household water use since 1999, which has been attributed to the adoption of water-efficient fixtures and appliances [13].

2.1. Permanent Supportive Housing

PSH is a housing-first intervention designed to provide long-term, affordable housing in conjunction with voluntary supportive services to individuals experiencing chronic homelessness and complex health or behavioral needs. It has proven effective in reducing housing instability and improving health outcomes, particularly for individuals with disabling conditions [14, 15]. PSH is grounded in the principle that stable housing is foundational for recovery, well-being, and community reintegration [16]. Non-intrusive methods are particularly attractive in PSH contexts, where privacy, cost, and resident stability are significant concerns. Research has demonstrated that when users are presented with feedback about their water use, especially in real time, they are more likely to adopt conservation behaviors [1, 17].

While use of smart home technology in supportive and elder care housing has grown [18–26], research at the intersection of residential water end uses and occupant behavior in PSH specifically remains scarce. The unique social, infrastructural, and behavioral characteristics of PSH demand attention distinct from conventional residential housing models. PSH units are often situated in multifamily apartment buildings, converted motels, or purpose-built housing complexes. These buildings may house formerly unsheltered individuals, persons with physical or cognitive disabilities, veterans, or those with histories of substance use or mental illness [27]. Several key factors distinguish PSH as a residential setting:

- Intensive support needs, including healthcare coordination, case management, and assistance with activities of daily living,
- Atypical household routines, often shaped by irregular sleep, medication regimens, or trauma-related behaviors [28],
- Aging or retrofitted infrastructure, in which sub-metering is rare and fixture-level monitoring is often unavailable [7, 29],
- Hybrid private-communal layouts, such as shared bathrooms or on-site laundry rooms.

These elements affect how water is accessed and used within PSH and challenge traditional assumptions embedded in residential end-use models, presenting important considerations for infrastructure operations and environmental and social sustainability.

Occupants of PSH often exhibit behavioral routines that differ markedly from general residential populations. These behaviors can include nocturnal activity due to insomnia, post-traumatic stress disorder, or substance use; atypical hygiene patterns, sometimes shaped by mental illness or trauma [30]; frequent bathing or faucet use associated with compulsive behaviors or symptom management; and adaptive strategies, such as using the shower as a private retreat or allowing water to run for white noise [8, 28]. Such behavioral signatures are not captured well by conventional end-use classification models, which tend to assume predictable diurnal patterns, typical household compositions, and normative appliance use. Even in standard Dutch households, water use displayed wide variability in event timing, frequency, and duration [8]; this variability is likely amplified in PSH contexts.

The prevailing models for disaggregating and interpreting water use rely on statistical regularities in duration, flow rate, and frequency [6, 7]. However, the behavioral heterogeneity of PSH residents, combined with infrastructural constraints, challenges these models; despite the growth of PSH as a housing model, few studies have explored water use as a behavioral indicator within these contexts. Much of the research to date focuses on clinical outcomes, housing retention, or cost-effectiveness [14, 31]. Other environmental sensing work has demonstrated that dashboards providing insights on occupant comfort (as measured from temperature, humidity) have positive impacts on well-being [23]. Effectively monitoring energy consumption at both building and neighborhood levels by identifying patterns, deviations, and abnormal behaviors in energy use relative to expected conditions is a scalable approach [32].

2.2. Typical and Atypical Behavior

In water demand modeling, 'typical' behavior is often defined by statistical central tendencies: average shower lengths, daily toilet flush frequencies, or expected time-of-day patterns. These norms are embedded in classification algorithms, simulation models, and demand forecasts [5, 8]. For instance, a morning peak in showering or a predictable evening dishwashing routine might be considered typical for a work week, and might differ from typical weekend behavior [33].

Conversely, 'atypical' behavior encompasses events or routines that deviate from these norms. Such 'atypical' events could include a toilet flush occurring hourly throughout the night, no shower events for several days, a 45 min faucet event at 3:00 AM, days with no water usage at all, or multiple laundry loads in quick succession. While such deviations might be flagged as anomalies by a rule-filtering mechanism, they could reflect critical dimensions of lived experience, such as health crises, compulsive behavior, or adaptive routines in response to trauma or environmental constraints [28]. Similarly, these 'atypical' events might reflect different schedules and contexts compared to single-family residential housing [9]. Atypicality is thus context-specific and isolating how much observed behavior deviates from expected behavior is a challenge. In the context of these complexities, studies have proposed using multimodal features, such as combining energy and water data, to better understand behavioral routines [34]. For instance, aligning hot water usage with electricity demand patterns might help distinguish between bathing and cleaning activities, adding nuance to classifications that otherwise rely only on flow rate and duration [7, 33, 35, 36] or electricity consumption [37, 38].

2.3. Occupant Behavior, Energy and Water Consumption

While infrastructure sets the bounds of what is possible, human behavior determines what actually occurs in resource consumption contexts. People shower, flush, clean, wash, and cook in rhythms shaped by habit, culture, mood, health, work schedules, household composition, and external signals like weather or price [5, 39, 40]. Unlike industrial or commercial systems, residential water and energy use is rarely optimized for efficiency instead reflecting embedded routines and decisions that are only loosely connected to conscious intentions. Numerous studies have shown that even within demographically similar households, usage can vary widely, particularly for discretionary end uses like bathing or laundry [8, 41]. This variability arises not only from appliance or fixture efficiency or occupancy but from behavioral frequency, duration, and sequencing.

2.3.1. The Hawthorne Effect and Behavioral Observation

Perhaps the most notable illustration of behavior changing under observation is the Hawthorne effect, originating from workplace studies in the 1920s, in which employees increased productivity simply because they knew they were being studied [42]. In the context of water and energy monitoring, the same principle applies: occupants might change their usage patterns when they know they are being measured, especially in pilot programs or research studies [5].

These conditions present both opportunities and challenges. Smart meter installations themselves might prompt conservation, especially when coupled with user-facing displays or feedback apps [43]. If the time scale is sufficiently long enough, behavior bias can fade and underlying tendencies emerge in user behavior [42].

2.3.2. Energy and Water Use as Joint Behaviors

Water and energy are often used together in households, and many key behaviors, such as showering, cooking, and laundry, involve both resources. For example, heating water consumes a large share of household energy use [37]. Understanding the timing and frequency of hot water-use events can therefore illuminate both thermal load and water demand. Previous work has demonstrated that incorporating energy-related features into water consumption models (such as electricity consumption from water heaters or washing machines) significantly improves the explanatory power of these models [34, 44]. Li *et al* [34] in particular showed that energy-use patterns were more predictive of water use than traditional demographic variables, suggesting that behavioral routines, inferred through joint data streams, can aid understanding household consumption and could be extended to reveal the converse.

The joint consideration of multiple data streams is crucial in supportive housing, where time-of-use and appliance-access patterns can differ significantly from normative assumptions. For example, laundry frequency might be higher due to hygiene concerns or lower due to physical limitations. By aligning energy and water data, researchers can uncover routine signatures that indicate health events, engagement levels, or the need for assistance [1]. This approach presents an opportunity to integrate metering into built housing stock as a promising pathway to realizing net zero-energy housing [45].

Many smart meter programs are predicated on the assumption that information changes behavior [46]. When users are shown how much water or energy they consume, particularly in comparison to neighbors or goals, they are expected to reduce usage; this assumption is only partially supported by the literature. Darby [47] classified feedback into direct (real-time data via displays/dashboards or apps) and indirect (monthly reports or billing comparisons). Direct feedback was more effective, particularly when paired with behavioral prompts like tips or challenges [47].

Machine learning and behavioral modeling increasingly seek to predict water use patterns from fine-resolution data, including flow signatures, temporal routines, and appliance correlations [4, 6, 48–50]. These models can estimate fixture use and timing, water consumption, behavior change over time, and presence of leaks or anomalies. However, such predictions, while powerful, come with caveats. First, models trained on typical households might not generalize to marginalized populations, shared living environments, or irregular routines. Second, predictions might be accurate without being interpretable; i.e. what looks like an 'anomaly' in data might be reasonable behavior in context. To address these issues, researchers recommend combining disaggregation algorithms with qualitative insights from residents or support staff [24]. Hybrid methods that blend statistical inference with ethnographic understanding are better suited to behavioral complexity [8, 29].

People tend to underestimate household water use by a factor of 2 on average, including significantly underestimating high water-use activities [51]; i.e. survey participants ($n = 1020$) estimated their water use to be half the actual amount. Beneath the surface of these ordinary water-use activities lies a complex landscape of human behavior that varies across individuals, households, and contexts. This behavioral diversity is particularly important in the context of analyzing residential water end uses, where assumptions of typicality can lead to blind spots and misinterpretations. Ultimately, interpreting occupant behavior is about understanding how people live, cope, and adapt and how infrastructure can better support them. In some contexts, stagnation time (defined as the time since an appliance or fixture was previously used) can provide evidence to discern between user groups and individuals and link individual activities to specific water end uses [52].

3. Materials and Methods

Understanding variation within residential water end uses is the first step in determining what constitutes typical behavior. The data we used throughout this study reflect the aggregate activity of several individuals in a household and do not necessarily attribute end uses to unique individuals. However, stagnation time (the time since a fixture or appliance was last used) can reflect different user activities for the same end use and could assist in credibly discerning end uses specific to individuals in the future [52]. In this study, we used a custom ally® smart water meter to record flow, temperature, and pressure data with 1 s resolution at the main supply pipe of a single-family, fully-detached residential study home in a medium-sized humid-temperate city in the Midwest United States. The ally® smart water meter measured flow within a range of 0.03–55 gallons per minute (GPM). Based on the approach from Bethke *et al* [33], disaggregation of the water time series data uses an event threshold of 0.1 GPM. The study home is representative of typical North American residential water use behavior [7, 13]. However, a single-family residential home does not necessarily represent the complete spectrum of residential water behaviors [9]. Although we expect PSH water use behavior to be distinct, an analytical framework will only be useful in PSH contexts if it can be demonstrated effectively in more typical standard residential water contexts.

3.1. Sub-daily and Weekly Analysis via Consumption Coefficient Profiles

We disaggregated and classified 1 s resolution flow data over an 8-week period (August to September 2024) into six end uses (toilet, shower, faucet, refrigerator faucet, washing machine, dishwasher; see figure 1) using a random forest classifier from Heydari and Stillwell [35] trained on 6-week water diary ground-truth data from the study home. While the smart water meter system measured data from January 2018 to February 2025, we focused our analysis on the 8-week study period with labeled end uses. We were able to discern between a total of 3963 water use events that were mapped to one of six end uses. All end uses were attributed to indoor water use with no water used outside the home. Similar to Mazzoni *et al* [8] yet different in underlying composition, we computed consumption coefficients c_t^k for an end use k at time t to analyze weekly consumption patterns across end uses. In the consumption coefficient, equation (1), the numerator contains the average hourly water consumption for each end use (e.g. dishwasher, faucet, etc) at a specific hour of the day, while the denominator normalizes this hourly consumption by comparing it to the total daily consumption for that end use.

$$c_t^k = \frac{\textit{Average consumption of end use } \mathbf{k} \textit{ during hour } \mathbf{t}\,(\text{gal})}{\textit{Daily average consumption of end use } \mathbf{k}\,(\text{gal})} \tag{1}$$

A consumption coefficient $c_t^k > 1$ for an end use k at hour t implies that the water usage attributed to that end use is greater than the daily average usage for that end use; i.e. that end use likely ‘dominates’ residential water consumption in that hour, thereby implying that individuals are engaged in activities with the fixture or appliance.

3.1.1. Classification Metrics

We employed metrics of precision, recall, F1-score, accuracy, support, macro average, and weighted average to assess the performance of the random forest classifier. The predicted classes from the random forest model are shown in figure 2, based on ground-truth data labels [7].

Precision: Precision is defined as the proportion of correctly predicted observations (true positives, TP) for a particular class to the total predicted observations for that class (sum of true positives and false positives, FP); equation (2),

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

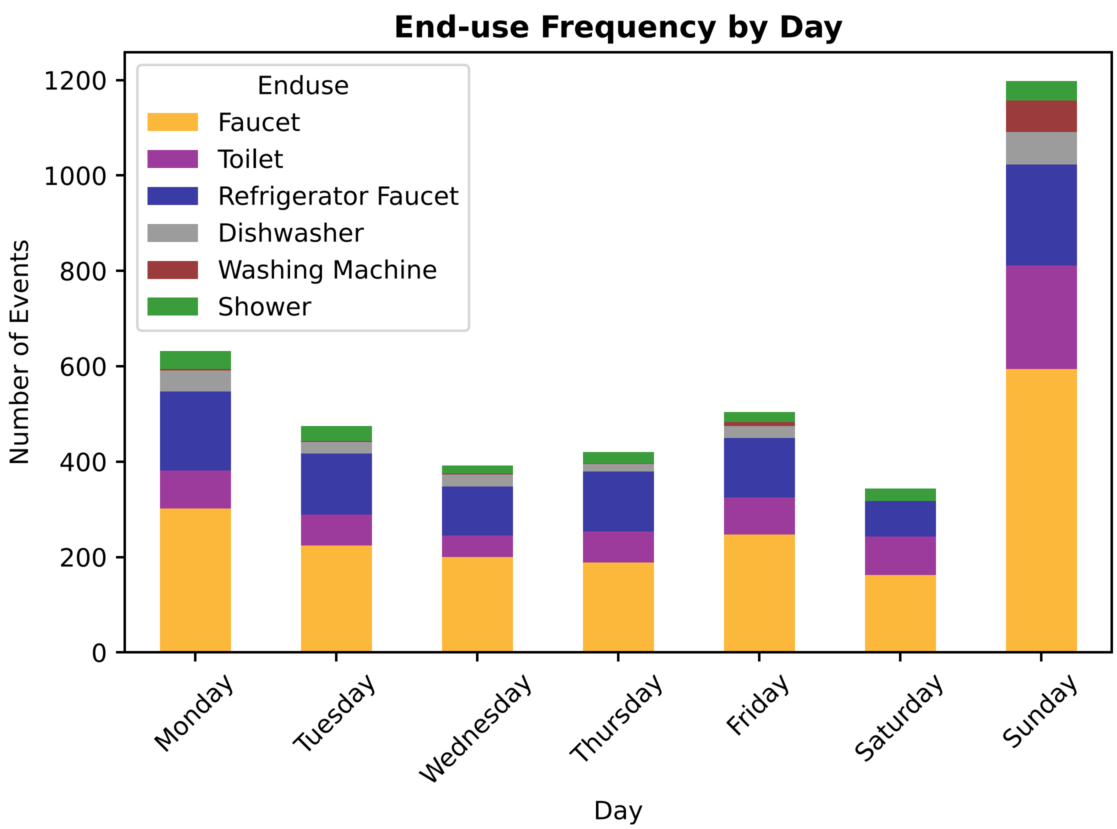


Figure 1. End-use frequency by day of week over the 8-week study period of August–September 2024.

Figure 2. Confusion matrix (0.70 train, 0.30 test) for the random forest model (based on ground-truth data labels from [7]) used to classify end uses for 8-week period.

High precision means that the classifier has a low false positive rate for that class. For example, out of 115 predictions for class 'f' [faucets] in figure 2, 107 were correct,

$$\text{Precision} = \frac{107}{107 + 8} = 0.93$$

Recall (Sensitivity): Recall as a measure of sensitivity is defined as the proportion of correctly predicted observations (TP) for a particular class to all actual observations of that class (sum of true positives and false negatives, FN); equation (3),

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

High recall means that the classifier has a low false negative rate for that class. For example, of 113 true samples for class 'f' [faucets] in figure 2, 107 were correctly identified,

$$\text{Recall} = \frac{107}{107 + 6} = 0.95$$

F1-Score: the F1-score represents the harmonic mean of precision and recall, providing a single measure of a classifier's performance for each class; equation (4),

$$\text{F1-Score} = 2 \times \frac{(\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})} \tag{4}$$

A high F1-score indicates a good balance between precision and recall. For example, for class 'f' [faucets]:

$$\text{F1-Score} = 2 \times \frac{(0.98 \times 0.95)}{(0.98 + 0.95)} \approx 0.98$$

Accuracy: Accuracy is defined as the proportion of correctly predicted observations to the total observations; equation (5).

$$\text{Accuracy} = \frac{\sum_i \text{True Positives}_i}{\sum \text{All Entries in Confusion Matrix}} \tag{5}$$

Accuracy measures the overall correctness of the classifier without regard for class balance or imbalance. For example the accuracy for this classifier is:

$$\text{Accuracy} = \frac{107 + 11 + 21 + 38 + 8 + 3}{203} \approx 0.93$$

Support: Support is defined as the number of true occurrences of each class in the dataset and provides context for evaluating precision, recall, and F1-score for each class. For example, in figure 2, class 'f' [faucets] support is 113, and class 't' [toilets] support is 46.

Macro average: The macro average reflects the unweighted average of precision, recall, and F1-score calculated independently for each class; equation (6). Because the macro average treats all classes equally regardless of their support, it can be useful when all classes are of equal importance.

$$\text{Macro Average} = \frac{\text{Metric}_1 + \text{Metric}_2 + \ldots + \text{Metric}_n}{n} \tag{6}$$

Weighted Average: The weighted average of precision, recall, and F1-score considers the support of each class and accounts for class imbalance by assigning more weight to classes with more samples; equation (7),

$$\text{Weighted Average} = \frac{\sum_{i=1}^{n} (\text{Support}_i \times \text{Metric}_i)}{\sum_{i=1}^{n} \text{Support}_i} \tag{7}$$

The interpretation of these classification metrics is presented in table S1 in the supplementary material with the classification metrics specific to this study summarized in table 1.

Table 1. Summary of classification metrics for residential water end-use prediction with the random forest classifier using ground-truth data from [7].

	Precision	Recall	F1-score	Support
Dishwasher (d)	1.00	1.00	1.00	3
Faucet (f)	0.93	0.95	0.94	113
Refrigerator Faucet (r)	0.85	0.92	0.88	12
Shower (s)	1.00	1.00	1.00	21
Toilet (t)	0.90	0.83	0.86	46
Washing Machine (w)	0.89	1.00	0.94	8
Accuracy			**0.93**	**203**
Macro Average	0.93	0.95	0.94	203
Weighted Average	0.93	0.93	0.93	203

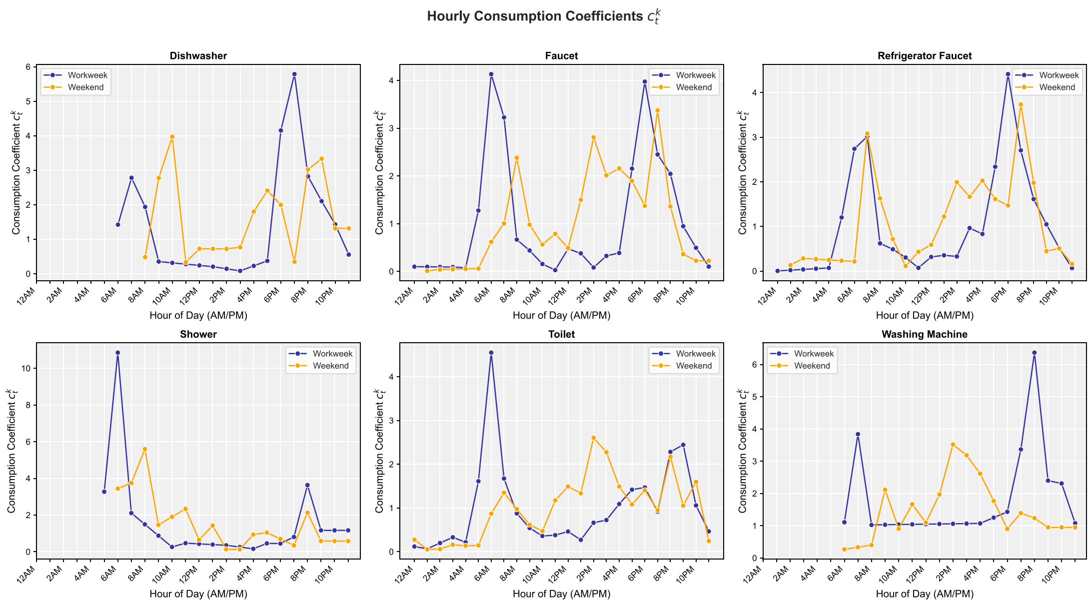


Figure 3. Hourly consumption coefficients, separated by workweek and weekend, vary by end use during the study period (August–September 2024). A consumption coefficient for end use *k* at hour *t* greater than 1 implies that the water usage attributed to that end use is greater than the daily average usage for that end use.

3.1.2. Typical and Atypical Hourly Water Consumption

We calculated hourly consumption coefficients, c_t^k, for workweek and weekend water use based on end uses classified by the random forest model for the study period of August–September 2024, as shown in figure 3. Consumption coefficients for the workweek and weekend reflect differences in when and how water is used. Most end-uses exhibit a lag on weekends suggesting later start and wake times for the residents in the study home. For the purposes of this work, an end-use consumption profile (counts of events and volumes attributed to an end use and referenced to a common timescale) was considered to be typical if it fell within 2-sigma (i.e. two standard deviations) of the average end-use consumption profile for comparable time periods. In time-series behavioral monitoring, thresholds relative to σ are common, but choosing them is a modeling decision. Rules (e.g. zones defined relative to standard deviations) are used to flag abnormal vs. expected behavior in time series data, using $\pm\sigma$ thresholds to classify 'expected' vs. 'unexpected' behaviors in longitudinal measurements [53].

3.2. Exogenous Maybes, Endogenous Origins: A Difference-in-Differences (DiD) Analysis

The DiD technique [54] (see supplementary material) is an econometric tool that can be used to estimate the causal effect of an intervention or treatment by studying the effect of a 'causal' (explanatory) variable on treatment and control groups. DiD, and not a single-year comparison, is a good tool for exploring the effect of exogenous variables on end uses because it removes noise from any would be confounders such as household idiosyncrasies, premise plumbing characteristics, occupancy affected by holidays, etc. The two-step difference removes *aggregate time shocks* that would affect, for example, both

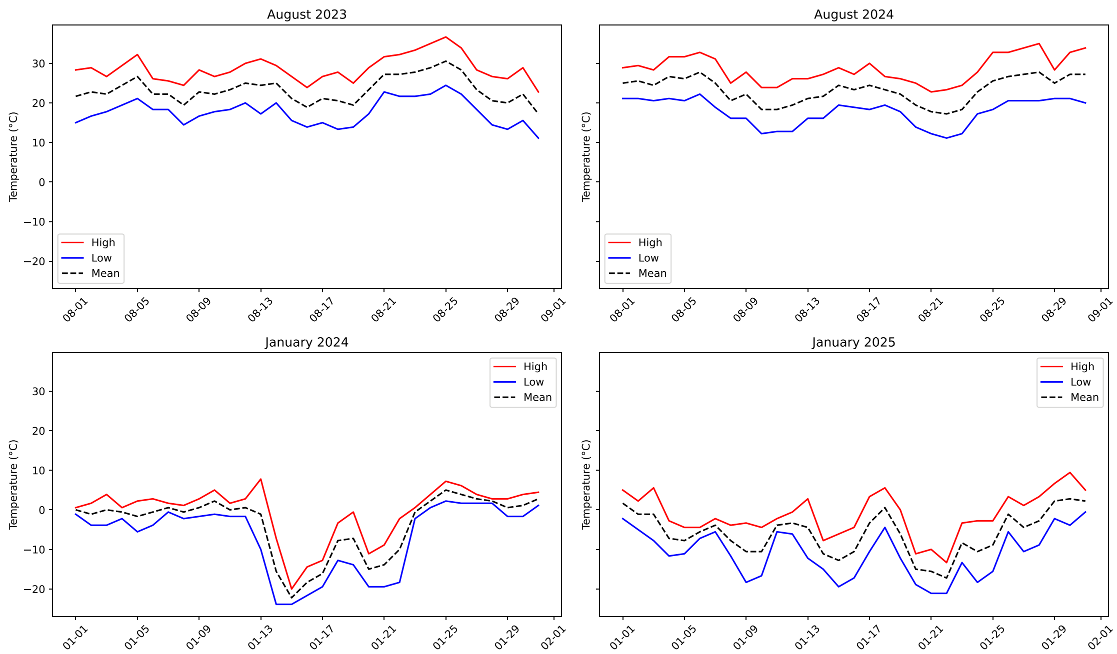


Figure 4. Daily temperatures for warm (August; top row) and cold (January; bottom row) months for the difference in differences (DiD) approach (data from [55]).

warm and cold months equally such as changes to water tariff charges, fixture upgrades, increased sensitivity to conservation, etc. What remains is the incremental change in the cold-warm gap attributable to the altered outdoor-temperature profile between the two years.

We employed this DiD technique to assess if colder weather explains the longer average shower durations observed in winter months as compared to summer months for the study home in the Midwest United States. The tangential association between longer shower duration and colder weather was reported by Ibáñez-Rueda *et al* [10], finding that individuals tended to take longer showers during winter months: the average shower duration was 11.6 min in winter, compared to 8.8 min in summer. This seasonal variation suggests that colder weather influences individuals to spend more time in the shower. We assessed the effect of average outdoor temperature on shower durations using data for 81 days across 16 weeks from warm (August) and cold (January) months across several years (months from 2023, 2024 and 2025; shown in figure S1 in supplementary material) with the pre-treatment period being before August 2024 and the post-treatment period starting from August 2024. While small in magnitude, the pre and post periods for the DiD approach were selected based on the difference between the average daily temperatures for these periods (figure 4), which set up the DiD such that the causative effect of longer shower durations would map to even colder temperatures in the post period (January 2025) as compared to the pre period (January 2024).

On average, shower durations for the analyzed months were greater during colder months compared to warmer months, shown in figure 5. Additionally, the shortest and longest duration showers were generally longer during cold months compared to warm months. Average volume per shower event was also greater during cold months compared to warm months, motivating statistical analysis through the DiD approach; see additional figures in supplementary material.

As an econometrics regression approach, the DiD method enables hypothesis testing around coefficients to quantify causal effects based on statistical significance.

Motivating questions:

Does the cold group (treatment) exhibit a different pre-to-post change in shower duration compared to the warm group (control)? In other words, is there an additional shift for the cold group from pre to post that does not occur (or not to the same extent) for the warm group?

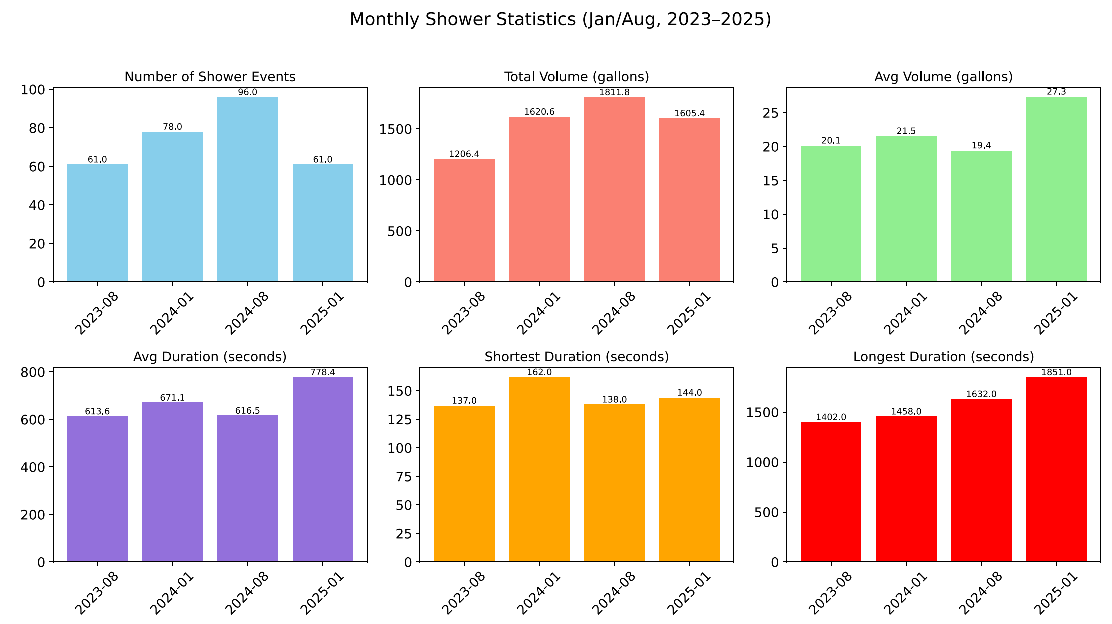


Figure 5. Monthly shower statistics for shower events, volume, and duration vary across warm (August) and cold (January) months for the study home.

Table 2. Description of variables used in the Difference-in-Differences (DiD) regression model.

Variable	Description
avg_duration_{it}	Daily average shower duration (seconds).
cold_{it}	Binary variable (1 if the day is in January, 0 if August).
post_{it}	Binary variable (1 for post-treatment (January 2025 or August 2024), 0 for pre-treatment (January 2024 or August 2023)).
$\text{cold}_{it} \times \text{post}_{it}$	The DiD interaction term capturing the additional effect for cold days in post-treatment.
Mean_C_{it}	Daily average outdoor temperature (in °C) as a control variable.
β_0 to β_4	Coefficients to be estimated.
ϵ_{it}	Error term.

Table 3. Interpretation of coefficients from the Difference-in-Differences regression.

Coefficient	Interpretation
β_0	Intercept (baseline average duration when cold = 0, post = 0, and Mean_C = 0).
β_1	Effect of the cold indicator on avg_duration, holding other variables constant.
β_2	Effect of the post indicator (the post-treatment period).
β_3	Interaction effect of being both cold *and* in the post-period.
β_4	Effect of Mean_C (additional continuous covariate). This coefficient describes how shower duration increases for every 1°C increase in the daily average outdoor temperature.

Regression Model:
The DiD regression model applied to average shower duration leads to the formulation shown in equation (8):

$$\text{avg\_duration}_{it} = \beta_0 + \beta_1\,(\text{cold})_{it} + \beta_2\,(\text{post})_{it} + \beta_3\,[(\text{cold})_{it} \times (\text{post})_{it}] + \beta_4\,(\text{Mean\_C})_{it} + \epsilon_{it} \tag{8}$$

where each observation i represents a single day (for August/January across 2023–2025), with variables further described in table 2 and coefficient interpretation listed in table 3.

Null and Alternative Hypotheses:

$$H_0: \quad \beta_3 = 0 \quad \text{(No additional pre–post change for the cold group beyond warm group)}$$
$$H_a: \quad \beta_3 \neq 0 \quad \text{(Non-zero shift for the cold group in the post period, different from the warm group)}$$

Treatment Group: Shower data for cold months (January 2024 and January 2025).
Control Group: Shower data for warm months (August 2023 and August 2024).

Time Periods:
Pre-treatment: Data from 2023 and 2024.
Post-treatment: Data from 2024 and 2025.

Assumptions of DiD:
1. Parallel trends: In the absence of the 'treatment' (effect of cold versus warm months), the change in shower duration over time would have been the same for both warm and cold months.
2. No other external factors (e.g. systemic lifestyle changes, fixture replacement or rated-flow changes, etc) significantly affect the results during this period.

3.3. Encoding Normality: Semi-structured interviews

The connection between smart water meter data, classified end uses, and typical versus atypical use patterns could serve as an effective alternative to daily well-being checks, which can be invasive and compromise privacy, in PSH. A smart water meter data-to-feedback alert pipeline could non-intrusively monitor water end-use behaviors and create feedback alerts to inform supportive services when interventions are necessary. This approach requires collaboration with social work experts familiar with supportive housing contexts.

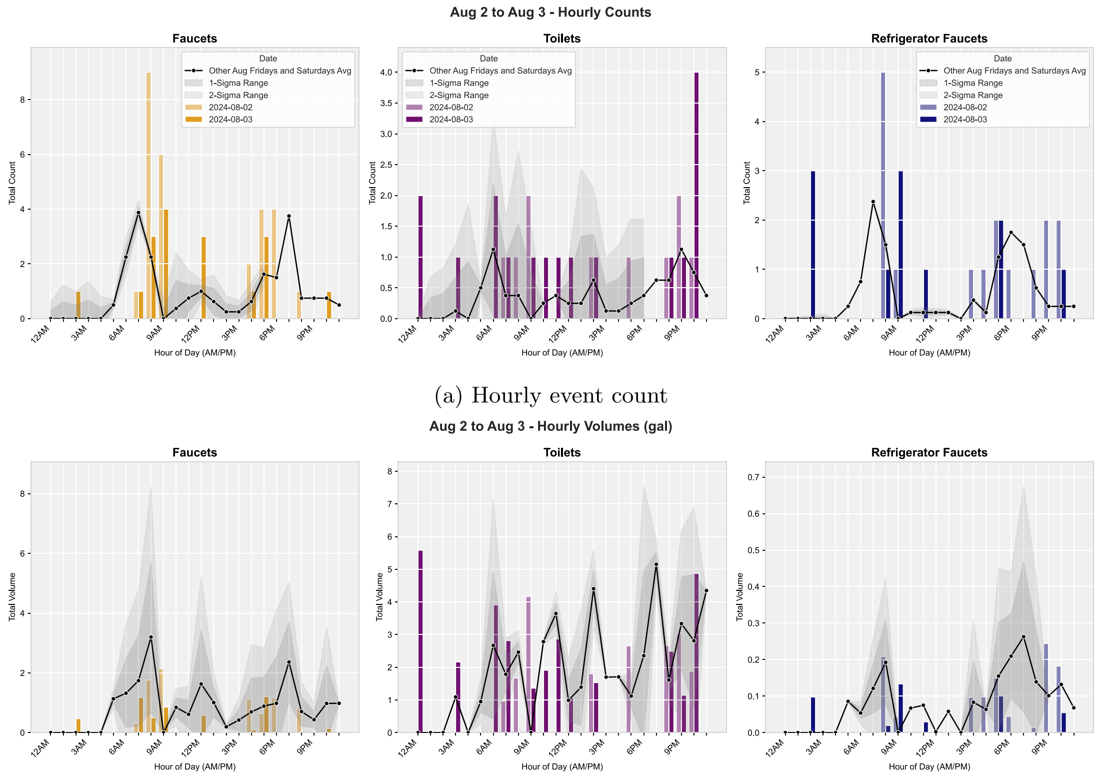
Creating a protocol to discern 'normal' and typical activity for unhoused and recently housed individuals as a unique population depends on deeper understanding of behaviors in response to housing insecurity. We invited experts in PSH and/or social work working in service organizations to participate in semi-structured interviews with members of the research team for this analysis. A background document was shared with potential participants. Research participants completed informed consent documents prior to engaging in 20–30 min of dialogue based on guiding questions around the possible role of smart home systems in PSH (see supplementary material). This protocol received an IRB exemption determination from the Office for the Protection of Research Subjects Institutional Review Board (IRB24-1517, Category 2).

4. Results

4.1. Water End Eses and Activities

We calculated and analyzed hourly end-use event counts and volumes (gallons) for three atypical conditions within the study home: overnight guests (2–3 August), Labor Day weekend travel, and an occupant home during the workweek (3–6 September). This approach demonstrated that for events that were known *a priori* to have occurred outside of a 'typical' routine, there were clearly visible event counts (figures 6(a) and 7(a)) and hourly volumes (figures 6(b) and 7(b)) associated with these events that fell outside this normally-distributed range. In figures 6(a)–7(b), these 'atypical' conditions are shown by consumption coefficients (colored bars) generally outside the 2-sigma shaded range around typical hourly consumption coefficients for the stated end use. However, these 'atypical' hourly event counts and volumes were not always outside the 2-sigma range for the entire duration of the observed atypical behavior, as shown for a different atypical event in figures 8(a) and (b), respectively.

Later start times for most end uses on weekends suggested that most occupants of the study home started their day later on weekends compared to workdays. Without some other input such as stagnation time, it was unclear what the likely latest start time for a particular end use was when using hourly consumption coefficients. During the study time period, Sundays had the highest volumes (1570 gal total over 8 Sunday observations) across all end uses, suggesting that most occupants were home. This water consumption on Sundays was 57.3% more than Mondays (997 gal total over 8 Monday observations),



(a) Hourly event count

(b) Hourly volumes (gallons)

Figure 6. August 2–3 represented a period of atypical late-night socializing with early morning end uses typically not observed during the study period, shown with colored bars generally beyond the 2-sigma range for typical conditions.

the second highest volume. Washing machine events were most frequent on Sundays, while dishwasher events were most frequent on Sundays and Mondays. Hourly counts and volumes can be better predictors of specific anomalous or atypical events rather than deviations from an observed average across similar timescales.

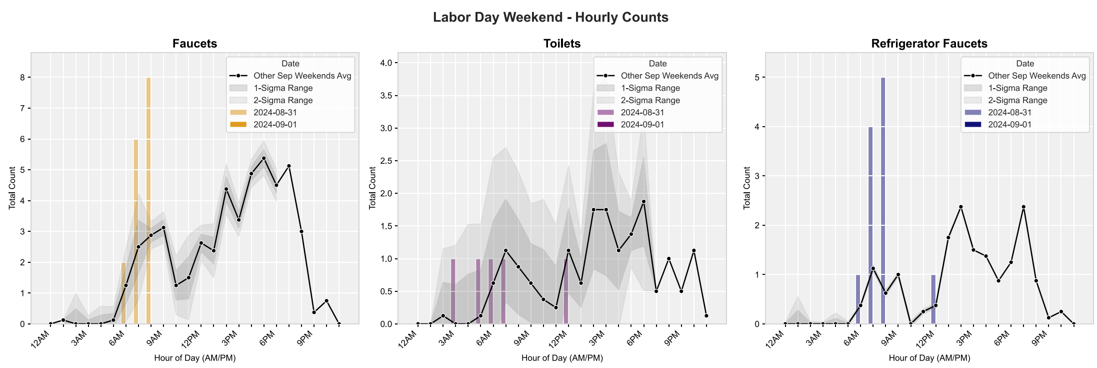
Our analysis was based on end-use activities at a multi-person dwelling; therefore, it is difficult to ascertain the end-use patterns of a specific individual. However, future work could define levels of caution based on atypical water behavior patterns and the anticipated severity of an event:

LOW : small magnitude leak (e.g., faucet not fully closed)
MEDIUM : anomalous long event (e.g., very long shower)
HIGH : large magnitude leak (e.g., burst pipe)

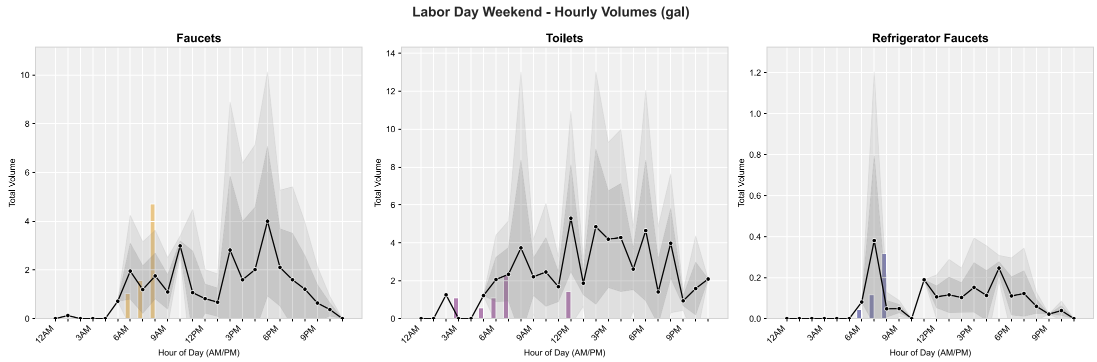
4.2. DiD Statistical Interpretation

Results of the DiD regression model demonstrated moderate statistical significance for shower durations in the study home. The regression model results are summarized in table 4 with further interpretation as follows:

- **Intercept ($\boldsymbol{\beta_0 = 687.6}$)**: β_0 represents the predicted shower duration (seconds) for a baseline day in warm (August) pre-treatment, assuming Mean_C = 0 °C. This value is the baseline average duration (in seconds) when cold = 0, post = 0, and Mean_C = 0.
- **Cold effect ($\boldsymbol{\beta_1 = -34.2}$)**: β_1 indicates that pre-treatment cold days (January) have, on average, 34.2 s ($p = 0.73$, not statistically significant) shorter showers compared to warm days. This value demonstrates that between warm (August) and cold (January) months in the pre period, holding temperature constant, shower duration in the cold month is ∼34 s less than the baseline shower duration.
- **Post effect ($\boldsymbol{\beta_2 = 2.4}$)**: β_2 represents the average change in warm days post-treatment (August 2024) compared to warm days pre-treatment (August 2023) of 2.4 s ($p = 0.96$, statistically insignificant).
- **Cold:Post (DiD Interaction) ($\boldsymbol{\beta_3 = 101.5}$)**: β_3 represents the estimated DiD effect, meaning post-treatment cold days experience an additional ∼102-s increase ($p = 0.12$, marginally significant) beyond the general trends observed in warm days.



(a) Hourly event count



(b) Hourly volumes (gal)

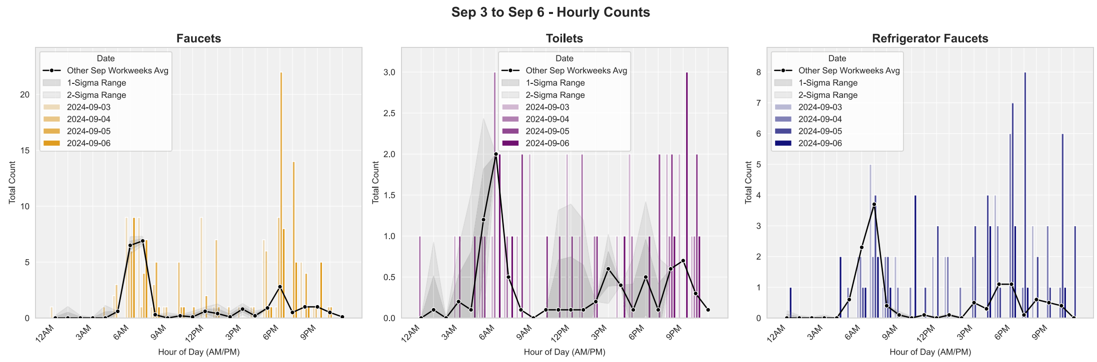
Figure 7. Labor day weekend represented a period when occupants were away from home, depicted by limited end use activity early in the day, shown with colored bars generally outside the 2-sigma range for typical conditions.

- **Mean_C effect ($\beta_4 = -3.2$)**: β_4 suggests that for every 1°C increase in the daily average outdoor temperature, shower duration decreases by about 3.2 s, albeit without statistical significance ($p = 0.30$).

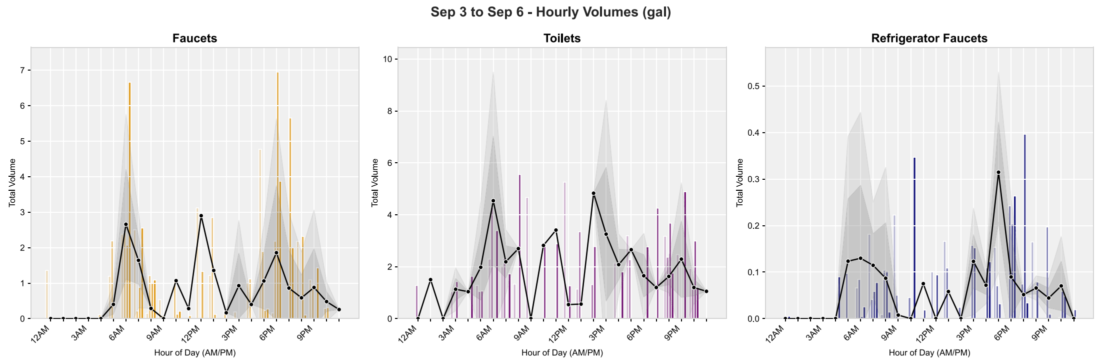
In addition to the statistical interpretation of coefficient estimates, the DiD model itself presents various statistical observations:

- $R^2 = 0.185$: Approximately 18.5% of the variation in shower duration is explained by the DiD model and included variables (cold, post, cold×post, temperature).
- Adjusted $R^2 = 0.142$: The adjusted R^2 indicates that the model explains a moderate share of variability after adjusting for four predictors, which is interesting considering one causal factor (colder outdoor air temperature) explains 14% of the variation in the daily average shower duration between warm and cold months.
- F-statistic $= 4.32$, $p = 0.003$: The overall model is statistically significant at conventional levels and as a whole has explanatory power.
- The interaction term (DiD coefficient β_3, $p = 0.123$) is statistically significant below the 15% level, with the value $\beta_3 = 101.51$ implying that from pre to post, the cold group's average daily shower duration increased by ∼102 s more than the warm group's pre-post change (holding temperature constant). This term is directionally positive, but somewhat inconclusive and should be interpreted as an exploratory result.

Overall, we observed tangible model significance (cold, post, and temperature collectively matter) and these results suggested an increase in shower duration for cold months post-treatment. Consequently, the intuitive understanding of taking longer showers in colder weather is likely, in part, due to the colder weather; however, there might be other variables at play such as standing in the shower for a perceived therapeutic effect, the presentation of seasonal affective disorder as a tendency to seek warmth, and other factors that cannot be neatly partitioned into a binary influence. The statistical significance of this causal effect was weak, which could be due to the small sample size, and better instrumentation could improve the robustness of this analysis. This analysis does, however, point to the association between exogenous factors and observed user behavior as it relates to specific water end uses. It remains to be seen if



(a) Hourly event count



(b) Hourly volumes (gal)

Figure 8. September 3–6 represented a period when at least one occupant was home during working hours. Some of the water end use event counts and volumes deviate from the 2- sigma range, but not all.

Table 4. Difference-in-Differences regression results for daily shower durations between August (2023 and 2024) and January (2024 and 2025).

	Coefficient	Standard Error	t	$P > \|t\|$	[0.025	0.975]
Intercept	687.6	79.7	8.6	0.00	528.9	846.3
cold	−34.2	100.2	−0.3	0.73	−233.8	165.4
post	2.4	45.8	0.1	0.96	−88.7	93.5
cold:post	101.5	65.1	1.6	0.12	−28.2	231.2
Mean_C	−3.2	3.0	−1.0	0.30	−9.2	2.9

N = 81, DF Residuals = 76, F-statistic = 4.32, Prob(F-stat) = 0.003, R-squared = 0.185, Adj.R-squared = 0.142

these results extend to other environmental variables and how these affects could be incorporated into thresholding baselines for typical behavior around water end uses.

4.3. Structured Interviews

We interviewed four practitioners using our semi-structured interview protocol. The practitioners' responses highlighted two core themes relating to the possible role of smart home systems in PSH:

1. **Agency & Mobility**
   One respondent explained that individuals in shelters have to deal with numerous roadblocks in their mobility and agency viz-a-viz housing vouchers and a nonexistent credit history. Case management is based on individualized needs with some individuals who receive vouchers needing minimal support and having had a long history of being employed, then having a medical issue, ultimately losing their job, and falling behind on their rent. These clients are ultimately evicted and require minimal assistance with a security deposit and can usually transition out of a shelter with adequate support. This condition mirrors lived experiences across the country [56]. Housing provides space and helps ameliorate problems that stem from sharing a crowded space with other residents in a shelter. Being housed in one's own space with access and boundary control can be vastly influential for overcoming any perceived 'difficulty'.

Support needs are on a spectrum and case management is often based on individualized needs, with some individuals coping with chronic homelessness and substance abuse and developmental disabilities requiring more administrative support in day-to-day affairs. These supports can include managing noise complaints from neighbors, dealing with the social responsibility of living in a larger apartment building, and adequately addressing issues as they arise to avoid minor solvable nuisances escalating into larger problems. Some occupants need support with budgeting, health insurance, and accessing other benefits. This support framework allows individuals in PSH to move from a scarcity-based survival mindset to an abundance-based growth mindset, which can help them focus on more important aspects of their life.

A diagnostic assessment of residents' water end uses could empower them to escalate maintenance issues with their landlord and address quality of life issues. This additional information could prepare them to take on the responsibility that comes with independently owning or renting a home. Furthermore, having detailed information about their end uses through a daily or weekly report could provide more actionable information and thus agency to change habits.

Well-being checks are useful in PSH because acclimating to a dwelling typically takes a long time for newly housed individuals, on the order of months and even years in some cases. Additionally the activity levels of residents could present varying baselines for the same resident so any kind of presumptive 'typical' activity patterns might have a multi-modal distribution. This complexity increases with individuals prescribed psychoactive medication, such as individuals with Bipolar Affective Disorder (BPAD). These individuals might not follow a regular expected activity pattern and their typical water end-use activity might not follow a predictable storyline to an outside observer. This aspect could be mitigated by using other consumptive features like lighting ON/OFF states, electricity consumption data, and heating/cooling demands.

2. **Trust**

Additional respondents stated that it is critical that residents be educated and informed about smart water meter sensing equipment monitoring their appliance/fixture usage. An opt-in framework for residents who will be explicitly made aware of the meters connected to the water main supply is an important component of smart metering in PSH. Case managers also assess what level of support residents require (food-purchasing assistance, health insurance, filing for disability, etc) and then match services to those needs.

The space between over- and under-explaining is challenging as occupants should not feel misled in their water consumption being monitored but should rather view it as an aid that could assist a case worker in following up with them if a troubling signal is reported (e.g. no shower activity for several days). Hyper-monitoring activities and using that information as a basis for disciplinary action when it is not warranted breaks trust and erodes any confidence and sense of security residents have developed in their housing arrangement. Residents need to feel a sense of ownership and control over their space so that they are comfortable letting in other individuals and building routines (primitive levels of Maslow's Hierarchy).

Some newly-housed individuals are much more conscious of their water use since they might not have previously had sufficient water available to tend to their water, sanitation and hygiene needs. As such, when they feel secure in their environment, some residents will understandably take time to transition, in some cases, from using a gallon of water a day to numbers more in line with typical residential contexts. Medically-fragile residents must feel safe to present behavior that can be mapped to any baseline. Trauma-informed housing can help case workers gain the trust of residents by being thoughtful of triggering environmental stimuli that might make them uncomfortable; metered usage helps replace regular surveys about consumption.

Ongoing case management can help identify relapses or conversely successful acclimation such as improved and consistent hygiene markers, regulating temperature around typical temperature set points for heating for individuals in colder climates, beginning to dispose of belongings that no longer serve a useful purpose, and other behaviors.

The themes across these interview responses illustrate the difficulty in predetermining a rule-filtering algorithm (e.g. a 2-sigma approach based on consumption coefficients) or alert levels based on thresholding when mapping to 'typical' activity in the context of PSH because multiple 'typical' or 'atypical' conditions might exist over time. The small interview sample size ($n = 4$) constrains the generalizability of these findings, and their use in analytical frameworks without further inquiry entails a risk of over-interpretation that could produce misleading, non-replicable results.

5. Discussion

Smart water meters allow researchers to move beyond monthly consumption totals and instead examine temporal sequences and granular event-level data. For example, a 7 min shower at 9:26 AM followed by two faucet events and a toilet flush within the next hour might represent a typical sequence. These sequences encode behavioral routines, though they are often abstracted in models designed for aggregate prediction [4, 5]. However, residential water data can also be treated as traces of daily activity rather than de-contextualized flow rates [8]. In this framing, each event offers a behavioral clue: a long faucet event might suggest therapeutic use, an absence of usage might signal a crisis, and consistent daily patterns might indicate emerging stability in residents previously experiencing housing insecurity [28]. Traditional end-use classification models often assume 'normal' routines such as 1–2 toilet flushes in the morning, showering once daily, and dishes washed after a meal [41, 57]. These assumptions might not align with conditions in PSH contexts, where behavioral diversity is shaped by trauma histories, disability, service access, and infrastructure constraints.

Atypical patterns should not be flagged simply as anomalies, but as invitations to understand what underlies them [31]. Going forward, it would be prudent to integrate behavioral and social science expertise in smart meter analytics as a mechanism to understand what would otherwise be dismissed as anomalous behavior. Energy-related features such as electricity use for heating or appliance operation significantly improved the predictive power of household water consumption models [34], suggesting that multi-modal data integration, such as water, energy, and potentially environmental or social data, can support more robust behavioral inference.

5.1. Improving Feature Space

Using other inputs tied to other consumptive end uses like lighting fixtures or concurrent smart electricity meter data from electrical appliances in conjunction with end-uses from water fixtures [44] could refine a broader feature space for establishing consumptive patterns. This feature space could provide the granularity required for a robust statistical learning framework that has the capacity to detect significant deviation from observed baseline(s). Multiple baseline activity levels for a particular end use along with acclimation (which can be a process on the order of months to years), relapses, and other complications necessarily affect human-built environment interactions.

5.2. Agent-based Models (ABMs)

ABMs can simulate the diverse behavioral patterns of occupants, which can be useful for realistic building performance and simulation of emergent phenomena associated with interactions between agents and their environment [58]. As a simulation technique, ABM represents individual entities ('agents') as autonomous actors with defined behaviors, preferences, and decision-making rules. This approach allows each agent (i.e. building occupant) to interact dynamically with both their physical environment and other agents over time. Unlike traditional aggregate or deterministic models, ABMs are well-suited to simulate the heterogeneity, adaptability, and emergent behavior patterns of real-world occupants [59].

An ABM approach could be useful in the case of PSH, where occupant behavior often departs significantly from normative residential patterns due to factors like trauma, disability, or irregular daily routines. Such a model would require detailed, heterogeneous data to represent individual occupants and their interactions with buildings. Key inputs include:

- agent attributes and states (e.g. demographics, health or stress conditions, daily routines)
- behavioral rules (e.g. when and why agents use water, schedules for when to bathe/cook, triggers such as hygiene after returning home, medication routines, etc)
- interaction structures (agent-environment and agent-agent interactions)
- building and system data (plumbing layouts, fixture characteristics)
- contextual drivers (e.g. weather, schedules)

Importantly, these model inputs would also require fine-resolution consumptive data (water and energy) alongside model calibration and validation [60, 61]. These elements allow ABMs to simulate realistic and emergent patterns, such as late-night showers or repeated toilet use, which are especially relevant in PSH contexts.

Each resident could ideally be represented as a distinct agent with individualized schedules, health needs, and interaction histories. These agents could generate specific water-use behaviors that could be explicitly modeled as intentional actions rather than anomalies or atypical behavior. For instance, water end-use events such as a 20 min faucet flow at 3:00 AM could be understood through the lens of agent intent, which could be a therapeutic coping mechanism or a behavioral expression of stress. These simulated behaviors could also be aligned to disaggregated water data streams. However, this approach also presents challenges; ABMs are computationally intensive and rely on extensive validation datasets that might be difficult and invasive to obtain from new residents. These considerations are contextually important regarding PSH when developing a framework of possible feedback between a new occupant and existing building affordances.

5.3. Limitations

Without more data it cannot be conclusively held that the study home behavior (i.e. fully mobile occupants mostly following a regular workweek-weekend routine) is representative of other similar residential living spaces. However, other work using data from the study home has demonstrated that the water end use activity from this home does generally align with REU2016 data [7]. Scaling technologies like smart water meters in PSH can be cost-prohibitive and at times the affordances offered by existing infrastructure may not support their deployment [62].

The study period we chose for the DiD analysis was constrained to months for which water meter data were readily available; improved instrumentation, more data points across similar warm-cold month pairs, and comparisons with warm-warm and cold-cold DiD aggregates could improve the robustness of the work done and provide a path forward for understanding occupant-built environment feedback. Differentiating results by age group or gender is beyond the scope of this non-intrusive analysis; the disaggregation mechanisms cannot inherently differentiate between end users although there are several years of end-use data to potentially sample from.

Using only *a priori* atypical events biases interpretation for consumption profiles when using dispersion so it might be prudent to use other dispersion ranges to similar *a priori* events to assess how much of the atypical activity is captured through a consumption coefficient approach in future work. All atypical events did not fall outside the 2-sigma range, which is a limitation of using this statistical approach. Given that the coefficient of determination for the DiD model was relatively low (0.185), the overall model has limited explanatory power. Additionally, the relatively small dataset risks overfitting, which could be mitigated by including more study homes in future work.

6. Conclusion

Residential water usage provides key insights about occupant behavior and well-being, which can aid decision making. Using water meter data from a residential home in the Midwest United States, we analyzed how atypical activity could be evaluated considering dispersion, the effects of exogenous variables on consumptive end uses, and normative behavior for individuals.

We explored three research questions, with the following findings:

1. *What aspects of water end uses can be used to ascertain behavioral information about the individuals performing those activities? Are statistical measures (such as dispersion) a good way to discern 'typical' and 'atypical' activity?*
   Water consumption at specific end uses can exhibit a discernible and repetitive consumption profile under various external conditions. In the study home, these profiles were noticeable in the characteristic workweek-weekend consumption profiles with a lag in start times for end uses on weekends. Some, though not all, atypical activities were captured in the dispersion of end uses beyond a 2-sigma range based on consumption coefficients.

2. *What, if any, is the effect of exogenous environmental variables such as outdoor air temperature on residents' specific end uses? How much of the variability in water consumption from a specific end use can be explained by some external variable?*
   Exogenous variables do appear to affect how occupants interact with water fixtures, specifically in the case of showers. It is important to isolate the effects of these influences if the analysis is performed on a time scale that would amplify their presentation.

3. *What is normative behavior for individuals moving or acclimating to PSH?*
   While most behavior is understood to be conscious and the result of willful intention, the way in which individuals interact with water fixtures is also a consequence of their wider sense of self. For example, individuals on psychoactive medication will likely exhibit different levels of activity as normal and typical for them depending on their medication regime and adherence to set routines.

Additionally, some individuals have more than one distinct baseline, and those baseline activity levels might also shift with time.

We conclude that prescriptive measures of atypical end use activity are not all-encompassing in capturing events and associated behaviors that are present in day-to-day routines. Due to the nature of acclimation, residents in PSH should not be expected to exhibit normative behavior underpinned by a consistent baseline: capturing truly atypical activity might best be abstracted from ABMs and agentic simulations. Exogenous variables can have a noticeable yet not always willful impact on end use consumption characteristics and all analyses should either be performed at timescales sufficient to account for this effect or otherwise explicitly constrain interpretation of consumption to this context. This work contributes to social sustainability by providing frameworks that support equitable and inclusive residential water systems that promote occupant agency.

This study provides the broader context and path-lighting for performing more feature-rich analyses for credibly connecting occupant behavior in PSH to end user water consumption and providing actionable insights for residents and case-managers alike.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://stillwell.cee.illinois.edu/data/.

Supplementary material available at https://doi.org/10.1088/2634-4505/ae1e9c/data1.

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Author contributions

Hassaan Khan 0009-0009-8592-6956
Conceptualization (equal), Data curation (equal), Formal analysis (lead), Investigation (lead), Methodology (lead), Validation (lead), Visualization (lead), Writing – original draft (lead), Writing – review & editing (equal)

Ashlynn S Stillwell 0000-0002-6781-6480
Conceptualization (equal), Data curation (equal), Formal analysis (supporting), Funding acquisition (lead), Investigation (supporting), Methodology (supporting), Project administration (lead), Resources (lead), Supervision (lead), Validation (supporting), Visualization (supporting), Writing – original draft (supporting), Writing – review & editing (equal)

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