ENVIRONMENTAL RESEARCH
INFRASTRUCTURE AND SUSTAINABILITY

PAPER • OPEN ACCESS

Understanding water consumption in a semi-permanent residential context through university student housing showers

To cite this article: Victoria V Otrubina *et al* 2025 *Environ. Res.: Infrastruct. Sustain.* **5** 015022

IOP Publishing Environ. Res.: Infrastruct. Sustain. 5 (2025) 015022 https://doi.org/10.1088/2634-4505/adbd6f

ENVIRONMENTAL RESEARCH
INFRASTRUCTURE AND SUSTAINABILITY

OPEN ACCESS

RECEIVED
25 October 2024

REVISED
20 February 2025

ACCEPTED FOR PUBLICATION
6 March 2025

PUBLISHED
17 March 2025

PAPER

Understanding water consumption in a semi-permanent residential context through university student housing showers

Victoria V Otrubina, Zahra Heydari and Ashlynn S Stillwell*

Civil and Environmental Engineering, University of Illinois Urbana-Champaign, Grainger College of Engineering, 205 N Mathews Ave, Urbana, IL 61801, United States of America

* Author to whom any correspondence should be addressed.

E-mail: ashlynn@illinois.edu, votrub2@illinois.edu and zahra2@illinois.edu

Keywords: showers, water use, synthetic data, residence halls

Supplementary material for this article is available online

Abstract

Understanding shower habits is critical for developing effective residential water conservation and efficiency strategies. Previous research has focused on single-family homes, but less is known about shower behavior among college-aged individuals in university student housing. This study examines the shower habits of students at the University of Illinois Urbana-Champaign, comparing them with U.S. single-family residential households regarding shower duration, time-of-day, and day-of-week. Using Conditional Tabular Generative Adversarial Networks to generate synthetic data, we address sample size limitations and confirm the validity of our results. Our findings reveal that student housing showers tend to be longer in duration and more variable compared to showers in single-family residences. Unlike the predictable routines seen in single-family homes, student housing inhabitants display less consistent showering habits, with different time-of-day patterns that challenge typical conservation incentives. Major shower events also occur more frequently before weekends in student housing. These insights emphasize the need for tailored water conservation strategies in semi-permanent residential settings. We recommend further exploration of targeted interventions, including educational campaigns, real-time feedback mechanisms, and gamification, to foster sustainable shower habits among university students. This study contributes to sustainable water management by providing actionable strategies within a sociotechnical systems lens for enhancing water conservation in semi-permanent residential contexts.

1. Introduction

Showers are part of a daily routine for nearly two-thirds of all United States residents [1]. The typical shower spans roughly 8 minutes, using an average of 16 gallons of water per event [2]. For many, skipping a single shower can cause social and physical discomfort and disrupt the day-to-day routine [3]. Beyond the need to uphold cultural appearance and cleanliness standards, additional contributors for daily shower usage include the associated energetic boost, hygienic needs from exercise, and availability of showering fixtures in an individual's environment [3]. Shower water consumption is not trivial when considered against the backdrop of escalating water scarcity [4], highlighting the urgent need for targeted conservation and efficiency efforts within a sociotechnical interface.

Extensive water conservation and efficiency research has been undertaken since the 1990s, following water distribution systems shifting towards demand-oriented delivery rather than base supply cost recovery via general taxation [5]. The 2016 Residential End Uses of Water study (REU) provided an updated analysis of 17 000 shower events in single-family residential homes across the United States and Canada [6]. The REU study findings illuminate the patterns of shower usage within residential households, offering a benchmark for comparison to shower water use in other residential settings, such as university residence halls.

Approximately one-third of all shower events in the United States occur in the morning, aligning with the typical weekday work schedule [1]. These users exhibit a consistent pattern of routine behavior that is often limited by external professional or academic commitments. In such contexts, advocating for water and energy conservation through showers specifically poses challenges, as many users perceive morning showers as indispensable, rendering habit alteration difficult [7, 8]. In conservation contexts, consumers often identify major sustainable habit changes for others to implement while justifying maintaining their individual usage as essential [9].

Conversely, full-time students in U.S. colleges and universities are not bound by the same rigid schedule as their full-time working counterparts [10]. Their academic obligations vary, with class schedules and commitments dispersed throughout the day. Additionally, students partake in a range of after-school assignments and activities that extend beyond standard professional working hours [11]. These differences could noticeably affect college-aged individuals' water and energy consumption patterns. Comparing student shower water use to that of single-family residential households can highlight unique behaviors and peak usage time, identifying specific opportunities for water-saving interventions.

While extensive conservation strategies have been successfully applied within traditional residential settings [12, 13], a notable gap exists in applying these strategies to semi-permanent living environments such as university residence halls [14, 15]. These environments, representing long-term but impermanent housing, can foster unique adjustments to daily routines, rendering standard conservation measures less effective. The transient nature of residence hall or dormitory living, coupled with the distinct social and academic rhythms of college or university life, suggests that students might prioritize convenience and immediacy over conservation, especially in the absence of direct utility costs. This divergence in living conditions and motivational drivers necessitates a tailored approach to promoting water conservation in university residence halls. Understanding the multifaceted relationship between individual behaviors, environmental policies, and conservation outcomes is crucial for devising effective strategies [16]. Targeted interventions can be valuable, combining behavioral science and technological innovations to promote water and energy conservation across different residential settings [17] . By comparing shower usage behaviors and patterns between students residing in university housing and the general population of U.S. single-family homes, we aim to illuminate these unique behaviors as valuable context for informing effective conservation interventions with university students.

Traditional methods of data collection face limitations in capturing the full spectrum of showering behaviors within residence halls [18], including challenges related to sample size and the representativeness of collected data. In this study, we employ synthetic data generation techniques to overcome these obstacles [19, 20]. By simulating shower events based on observed patterns, synthetic data offer a means to extend our understanding beyond the constraints of direct measurement, providing a robust foundation for analyzing shower usage among university students.

We implemented end-use water metering of shower events within a sample of the student population housed at the University of Illinois Urbana-Champaign (UIUC). Through our study, we specifically answer the following questions:

(i) What are the behaviors and patterns of shower usage among residents of university student housing?
(ii) How can synthetic data expand data availability while accurately representing student shower behavior dynamics?
(iii) How do student shower behaviors and patterns compare with those observed in U.S. single-family residential settings?

Through this exploration, we contribute to the broader discourse on water conservation, offering insights into the specific context of university student housing. Targeted conservation strategies can lower operational costs associated with water usage and maintenance, thereby allowing universities to allocate resources more efficiently [21]. This research reveals nuanced opportunities for promoting water conservation in semi-permanent living environments via measured and synthetic data in comparison to U.S. residential homes.

2. Background

2.1. Residential water conservation and efficiency

Freshwater scarcity has emerged as a critical catalyst for conservation efforts. In the U.S. Midwest, traditionally abundant in water, droughts and management challenges have significantly strained water resources [22]. This shift, coupled with urbanization, presents ongoing challenges in water distribution management for urban planners [23]. Additionally, the public's focus on municipal governance failures, exemplified by the Flint, Michigan water crisis, has heightened awareness of water resource management [24]. Water and energy challenges also motivated policy change, including limiting showerhead flow rates to a maximum of 2.5 gallons per minute (gpm) to reduce water use [25]. The Energy Policy Act of 2005 further extended these restrictions to other household fixtures and appliances, setting benchmarks for water and energy efficiency while ensuring service quality [26].

These regulatory measures have tangibly reduced indoor household water consumption, with a notable 22% decrease reported between the 1999 and 2016 REU studies [2, 6]. However, despite advances in efficiency, an average U.S. household can still lose up to 180 gallons of water per week through leaks, defective equipment, and inefficient behavior [13, 27, 28]. Therefore, behavior change is a valuable approach to reducing water use, with showers identified as primary consumers in residential settings [29]. As public climate consciousness grows [30, 31], there is increasing recognition of the need for water and energy conservation. The interplay between water and energy usage, often referred to as the energy-water nexus, is particularly relevant in the context of hot water use, especially in showers [32, 33].

Previous studies on residential water consumption have predominantly involved voluntary participants, often already inclined towards resource conservation [5, 34, 35]. This self-selection bias complicates the generalizability of findings [36, 37]. While financial incentives are typically seen as primary motivators for adopting sustainable technologies, they are less effective when marketed as the sole benefit [16]. Participants in sustainability-focused studies acknowledge the financial benefits but express a stronger commitment to environmental conservation [16]. This dynamic suggests a potential Hawthorne effect, where participants modify their behavior in response to being monitored [38]. Moreover, individual political beliefs significantly influence attitudes towards climate change and resource conservation, an important consideration in developing public conservation programs [39].

In households not engaged in water and energy savings studies, budgetary considerations often dictate smart resource utilization [39]. The ongoing scrutiny of consumption behaviors fosters a conscious link between actions and financial repercussions [40]. Direct and immediate feedback on the outcomes of one's actions establishes a robust internal association between behavior and its consequences [41]. For instance, participation in auto-pay billing systems, which eliminates detailed water usage data, has been associated with a 2%–3% increase in water consumption [42].

2.2. Temporary residences

Not all water and energy consumption in the built environment takes place in permanent residential settings. Domestic and international travel frequently necessitates stays in hotels or other temporary residences, where different consumption patterns emerge [43]. In these settings, the typical financial feedback mechanisms of permanent residences are absent, altering the occupant's resource usage behavior.

In temporary accommodations like hotels, water and energy costs are typically included in the room rate, obscuring the financial impact of excessive consumption and often leading to diminished conservation efforts [44]. This lack of immediate feedback and/or cost implication often leads to minimal conservation efforts by guests. However, Tiefenbeck *et al* [45] demonstrated the effectiveness of real-time displays in the absence of financial motivations by installing Amphiro A1 smart shower meters in 265 rooms across six Swiss hotels, collecting 19 596 observations. These smart shower water meters provided real-time information on water usage, with the intervention display showing a polar bear on an iceberg that melted as water use continued, encouraging shorter showers. This intervention led to an 11.4% reduction in water-related energy consumption compared to the control group [45], demonstrating that conservation is feasible in non-permanent residences without financial incentives, paving the way for further research in similar settings.

2.3. Semi-permanent living

College and university housing accommodations present a distinct category of semi-permanent residences. In such settings, students experience a certain level of stability in their occupancy, albeit without the typical financial responsibilities for water and energy usage. This condition eliminates monetary incentives for conservation, and the prolonged stay potentially leads to regularized patterns of habitual shower use [15, 46]. In our study at UIUC, students may select housing in university residence halls or private certified housing, each with different operational models. Residence halls and private certified housing are both UIUC-approved living accommodations for students to fulfill the first-year live-on requirement (Student Code Part 2, Article 2; [47]), with residence halls owned and operated by University Housing and private certified housing owned and operated by various private entities. Unlike temporary residences, which lead to short-term deviations from typical residential water consumption [45], residence halls and private certified housing provide students with housing for the duration of the academic year, during which usage behavior becomes regulated [48].

The living arrangements in university residence halls vary, ranging from individual shower and bathroom units to communal showering spaces [49]. Limited personal space and shared living arrangements introduce various factors that can influence student water use behaviors [50–53]. Variables such as privacy, hygiene practices, and personal well-being can contribute to differences in showering habits [54]. Understanding the multifaceted relationship between individual behaviors, environmental policies, and conservation outcomes is crucial for devising effective strategies. Targeted interventions can be valuable, combining behavioral science and technological innovations to promote water and energy conservation across different residential settings.

Our study at UIUC reevaluates shower behaviors and water conservation within this unique living framework, aiming to understand typical behaviors and showering habits. We compare shower habits from semi-permanent university housing contexts with permanent single-family residential shower norms in terms of shower duration, time-of-day, and day-of-week, providing actual (i.e. measured) and synthetic data for university student shower events. These data provide context for water conservation recommendations in university housing environments.

3. Methodology

3.1. End-use shower metering

Smart water metering systems include devices that record and relay fine-resolution water consumption data in real-time or near-real-time to both utility providers and consumers, offering precise usage measurements and the ability to detect leaks swiftly [55, 56]. In residential environments, individual water meters have been increasingly utilized to monitor specific end-use consumption, particularly in shower fixtures, to more accurately discern behaviors [57, 58]. Within the context of university residence halls, these meters are indispensable for analyzing and specifying shower-related water usage from overall consumption, thus yielding detailed insights into the showering patterns of university students.

Three primary criteria guided the selection of appropriate meters for this study. First, the chosen shower meter had to be compatible with the standard showerhead design used in UIUC residence halls and private certified housing, specifically the Delta 2.0 gpm single-function showerheads. Americans with Disabilities Act-compliant hose-style showers were not included due to incompatible plumbing configurations. Second, the meter needed to accurately measure and record the flow rate and duration of shower events, differentiating them from possible leaks, to ensure accurate data collection. The final criterion was that the meters must be unobtrusive to both the user and the environment, ensuring minimal interference with regular shower usage. Effective feedback delivery is essential for linking user actions to resource consumption without eliciting negative reactions that could impede conservation efforts [59–61]. Ambient metering reduces the Hawthorne effect, where awareness of being observed alters behavior [60], highlighting its importance in capturing accurate water use behaviors unobtrusively.

Off-the-shelf ambient shower water meter options that met our specific requirements are limited. The Amphiro A1 meter, used in Tiefenbeck *et al*'s study [45], was ideal for feedback delivery but incompatible with standard size U.S. plumbing fixtures. Consequently, we selected the Pani Smart Water Monitor (figure 1), which records the start and end times of shower events and the volume of water used with a resolution of 0.1 gallons, transmitting the data to a smartphone or tablet app. Its unobtrusive design integrates seamlessly into the shower environments of both residence halls and private certified housing, requiring no plumbing expertise for installation and easy maintenance. We installed 15 Pani Smart Water Monitors across university residence halls and private certified housing.

The dataset generated by these meters includes three primary features: shower duration (minutes), time-of-day (hourly), and day-of-week. We used these features in subsequent synthetic data generation and analysis, keeping measured and synthetic datasets aligned.

3.2. Data collection challenges

Our selected Pani Smart Water Monitors met our study metering requirements, but also presented notable data collection challenges. One significant challenge we encountered was the meter's dependency on a continuous, password-protected wireless Internet connection for data transmission. UIUC's enterprise Wi-Fi network, lacking a user-input password, was incompatible with the meter's data acquisition software. Initial calibration was conducted using a personal hotspot to overcome this connectivity challenge. The Pani meters can store data for up to seven days, necessitating at least a brief connection to the calibrated network for data upload before automatic erasure. This constraint required weekly visits to each installed meter in the university residence halls and private certified housing for maintenance and reconnection to the hotspot network. Additionally, two AA alkaline batteries power each Pani meter, introducing power management challenges when recording several showers per day. During our study, we replaced batteries in the meters every 8–10 days, on average, to maintain functionality.

Figure 1. Pani Smart Water Monitor installed on a university shower fixture. (Photo credit: authors).

While these challenges with the meter's connectivity and power were effectively managed to ensure the reliability of the data collected, they also highlighted the potential for data variability and recording gaps in real-world settings. We collected 285 measured shower events across three locations: 241 events from Pennsylvania Avenue Residence Halls (Babcock and Saunders Halls; university residence halls) and 44 events from Presby Hall (private certified housing).

3.3. Student housing context

We installed Pani Smart Water Monitors at two UIUC residence halls and one private certified housing location. Both residence halls and private certified housing are forms of student housing but differ in amenities and configurations. Living options vary in amenities and cost, with some units offering additional facilities and reducing the student-to-restroom ratio from 8:1 (for typical university residence halls) to 3:1 (for typical private certified housing) [62]. Our study focused on two wings of the Pennsylvania Avenue Residences (PAR), Babcock and Saunders Halls, which house a diverse student population. Babcock Hall's lower floors host a Living-Learning Community focused on race and heritage dialogues, while Saunders Hall's upper floors cater to students interested in international issues and cultures [63, 64]. This selection prioritized diverse resident backgrounds in our study population. Additionally, Presby Hall was selected as a private certified housing location for its continuous meter operation and wireless connectivity, facilitating uninterrupted data transfer. Presby Hall also houses tenants by gender, enabling possible comparison of co-ed and single-gender living arrangements in future studies with additional data features [65].

Babcock and Saunders Halls have identical layouts, each with 8 separate shower and toilet units per floor, serving about 60 students for an average of 7–8 students per restroom. In contrast, Presby Hall's layout resembles an apartment complex, with a ratio of approximately 3 students per restroom, featuring more privacy. Throughout the study, we installed 1–2 meters in selected showers on different floors of Babcock and Saunders Halls. In Presby Hall, we installed 2 shower meters in units in Wi-Fi proximity to each other. Detailed schematic layouts of the student housing installations are in the Supporting Information (figure S1).

3.4. REU of water data

We analyzed shower usage data from the 2016 REU study as a benchmark for comparison to university student housing showers. The complete REU database includes observations measured at 737 single-family homes in selected U.S. and Canadian cities from 2012–2013 [6]. In the REU study, end uses (i.e. toilet, shower, faucet, clothes washer, leak, bath, dishwasher, outdoors, and other) were determined using flow trace analysis [6]. The REU flow trace analysis includes disaggregation and investigation by an analyst, with additional oversight from an independent analyst for quality control. Consequently, we assumed the REU data were representative of single-family residential water consumption in the United States and Canada with no adjustments or filtering of outliers necessary. We focused our analysis specifically on the detailed water consumption observations collected from 17 000 shower events in single-family residential homes [6], with features of shower event duration, water volume, flow rate, time-of-day, and day-of-week.

The REU shower dataset has an average shower duration of 7.02 min, with a standard deviation of 4.79 min. The REU shower observations also show typical morning and evening peak usage patterns, reflecting structured routines commonly observed in single-family households. By utilizing the REU data as a point of comparison, we highlight the unique behaviors of university students residing in semi-permanent housing.

3.5. Synthetic data generation

Collecting labeled data for water end-use consumption observations is a challenging and resource-intensive process [58, 66, 67]. This difficulty creates a significant bottleneck in the field, hindering both robust analysis of water consumption behavior and training of models that could enhance water demand management. Often, small sample sizes fail to adequately represent the overall population, leading to low generalizability [68]. To address this challenge, the realistic generation of synthetic data offers a potential solution. In the dynamic environment of university student housing, we implemented synthetic data generation methods to strengthen our analysis. One promising approach to synthetic data generation is the use of Conditional Tabular Generative Adversarial Networks (CTGANs) [69]. We employed CTGANs to create synthetic data to ensure that our analysis remained robust against potential irregularities, particularly when comparing our findings with existing studies. Generation and analysis of synthetic data also helped determine whether any observed deviations in shower duration or water usage patterns were attributable to the unique behaviors of university students, or simply a result of a limited dataset.

3.5.1. CTGANs and data generation

CTGANs, typically requiring large datasets for effective training, were suitable for our dataset characterized by simplicity with three features: duration (minutes), time-of-day (hourly), and day-of-week. The straightforward nature of the data reduces the complexity usually associated with training neural networks, making CTGANs feasible even with our limited dataset size. This study builds upon the work of Heydari and Stillwell [70], which demonstrated the effectiveness of CTGANs in generating synthetic data representative of water consumption data in small datasets. We extend the methodology by including both numeric and categorical data to focus on shower behavior patterns specific to university students and comparing these behaviors to single-family residential households.

In CTGANs, the discriminator function is implemented as a fully connected neural network with multiple hidden layers, enabling it to learn complex representations of the input data. The discriminator's weights are optimized by minimizing an adversarial loss function, including a cross-entropy term, which drives the network to assign high scores to real data and low scores to synthetic data. For generating synthetic tabular data with CTGANs, the input data are often represented as a matrix, with each row corresponding to a data point and each column to a feature. This matrix can be viewed as a single-channel image, where the rows represent the image height and the columns represent the width [69]. CTGANs have been implemented for synthetic water end-use data generation previously [70].

For the purpose of this study, 'synthetic residence hall data' refers to a combination of our actual collected data and the synthetic data generated using CTGANs, with the actual collected data referred to as 'measured residence hall data.' Specifically, we collected 285 shower events from residence halls and private certified housing at UIUC and then used these data to generate 59 batches of 285 synthetic shower events, creating a combined dataset of 17 100 shower events. This combined dataset allows for a near-equal-size statistical comparison against the REU data, containing 17 000 shower events.

Note that although the synthetic data are based on the original dataset, they do not merely replicate the same observations. Instead, CTGANs capture the statistical relationships and patterns present in the smaller sample to generate additional, representative data. This approach enriches the feature space, helps mitigate biases introduced by a small number of observations, and enables a more robust foundation for subsequent analysis.

3.5.2. Evaluation of synthetic data

We applied a two-step verification to ensure that the CTGANs sample generation batches were representative of the measured residence hall data. After training the model, we created batches of 285 synthetic shower events, including time-of-day (hourly), day-of-week, and duration (minutes) of the shower events. We then leveraged the open-source package tableEvaluator [71], a library that visually evaluates how similar a synthesized dataset is to actual tabular data. This visual evaluation served as an initial screening step to confirm alignment between the synthetic and measured datasets across key dimensions.

Since the visual evaluation does not provide a quantitative assessment, batches that passed this initial screening were labeled as synthetic class data, while the measured data were labeled as real class data. These labeled datasets were then used to train classification models to determine whether the models could reliably distinguish between real and synthetic data. Ideally, the classifier should perform no better than random guessing, indicating that the synthetic data exhibits characteristics similar enough to the real data that it is effectively indistinguishable.

We trained two classification models: a random forest classifier [72] and an XGBoost model [73]. The random forest classifiers were configured with 100 trees and evaluated using log loss, which measures the model's predictive performance based on the accuracy of its probability estimates. We did not constrain the maximum depth of the trees, allowing nodes to expand until all leaves were pure or contained fewer than two samples. The number of features considered at each split was set to the square root of the total number of features.

When evaluating our synthetic data generation, the dataset comprised equal parts of actual and synthetic data, labeled accordingly. This approach ensured balanced classes and prevented bias [58]. To ensure robust model performance, a five-fold cross-validation procedure was employed, where the entire dataset was divided into five equal parts, with each part used as a test set once, while the remaining four parts formed the training set. This validation allowed us to evaluate the generalization ability of the classifiers comprehensively.

We evaluated the classification models using the area under the receiver operating characteristic (ROC) curve (AUC), which plots the true positive rate (TPR) against the false positive rate (FPR). The TPR and FPR are defined as follows:

$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{1}$$

$$\mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{FP} + \mathrm{TN}} \tag{2}$$

where TP represents true positive values, TN represents true negative values, FP represents false positive values, and FN represents false negative values.

The AUC-ROC curve is not based on a single threshold; instead, it provides an indication of classifier performance over a range of varying classification thresholds. In this way, the AUC-ROC captures how well a classifier discriminates between the classes of interest. Conveniently, the AUC-ROC can also be interpreted as the probability that a randomly chosen member of the positive class will be correctly ranked before a randomly chosen member of the negative class. Therefore, an AUC-ROC of 1.0 indicates perfect discrimination between classes, while an AUC-ROC of 0.5 indicates random guessing [74].

To assess the effectiveness of our synthetic data generation, we employed the AUC-ROC as a key quantitative metric to measure the classifier's ability to distinguish between actual and synthetic datasets. Specifically, we aimed to achieve an AUC-ROC value close to 0.5, which would indicate that the classifier performs no better than random guessing, thereby suggesting that the synthetic data closely mimic the characteristics of the measured data. During the model evaluation process, we monitored the AUC-ROC across various models to ensure that the generated synthetic data were sufficiently similar to the actual data, thus confirming the intended equivalence.

4. Results and discussion

4.1. Shower event data collection and generation

Shower event data were collected from Saunders and Babcock Halls in PAR from 9 December 2021, to 6 April 2022, and from Presby Hall from 14 October to 28 November 2022. Despite challenges such as intermittent connectivity and meter issues, we successfully recorded 241 shower events at PAR and 44 at Presby Hall. Since the ambient water metering system only collected volume, flow, and timestamp data, the UIUC Institutional Review Board (IRB) determined that our study was not classified as human subjects research; documentation of this IRB decision is available upon request.

Given the limited number of observations, we generated a larger synthetic dataset using CTGANs to enable a more robust comparison with U.S. single-family REU data, which includes 17 000 shower events [6]. We generated 59 batches of 285 synthetic data points, simulating approximately 17 000 shower events. The synthetic data creation and subsequent validation were critical to ensuring that any further comparison to residential settings would be meaningful.

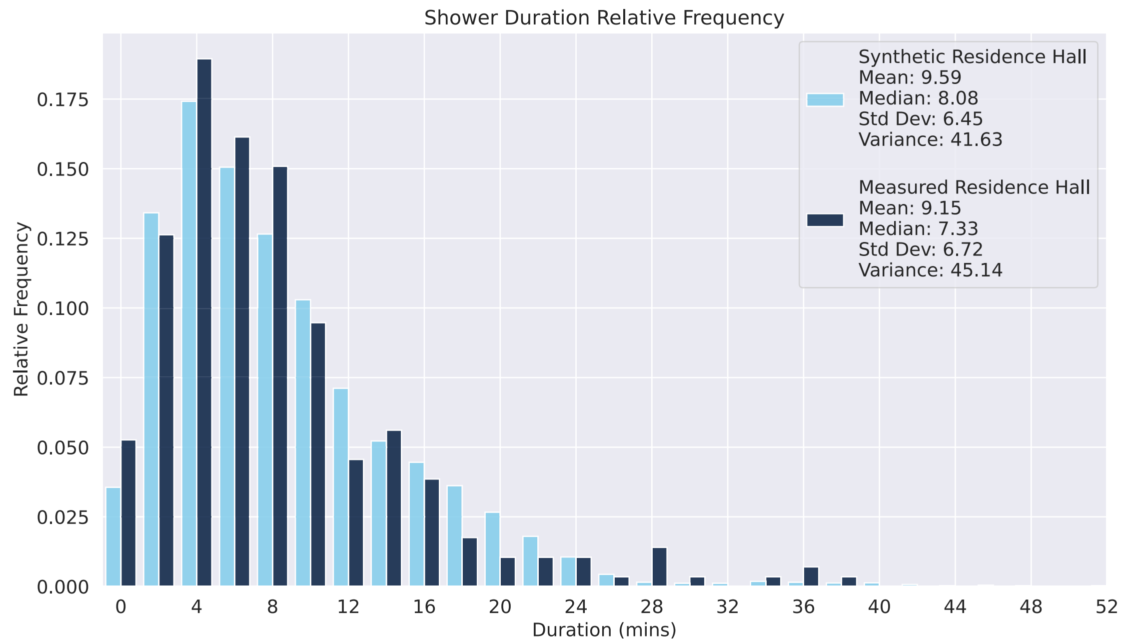

Figure 2. Shower duration relative frequency for measured and synthetic residence hall data.

4.2. Synthetic data analyses

Visual assessment of our synthetic data showed a strong similarity between the synthetic and actual datasets, effectively capturing the characteristics of time-of-day, day-of-week, and duration. We further validated the synthetic data generation with a random forest classifier and an XGBoost model. Both models were evaluated using a five-fold cross-validation procedure to ensure robustness.

We used the AUC-ROC metric to evaluate the ability of the random forest and XGBoost classifiers to distinguish between the actual and synthetic data. The AUC-ROC values for both models ranged between 0.50 to 0.57, indicating that the classifiers performed no better than random guessing in distinguishing between the two datasets. This outcome validates that the synthetic data are virtually indistinguishable from the actual data. Detailed results from the tableEvaluator assessments and the AUC-ROC analyses for sample synthetic data are provided in the SI (figures S1 and S2).

Figure 2 shows the shower duration relative frequency for both the measured and synthetic residence hall datasets. The measured residence hall data display a high concentration of shower duration around 8–10 min, and the synthetic residence hall data align closely, with a mean duration of 9.59 min, a median of 8.08 min, and a standard deviation of 6.45 min. The measured data have a mean duration of 9.15 min, a median of 7.33 min, and a standard deviation of 6.72 min. This close match indicates that our synthetic data accurately represent the actual shower durations observed in university student housing.

The event relative frequency by time-of-day for the measured and synthetic residence hall data is illustrated in figure 3. Both datasets show similar peaks around 12:00 PM, 5:00 PM, and 10:00 PM, reflecting the varied schedules and routines of university students. The consistency between the datasets further validates the reliability of our synthetic data generation process. The measured data show minor deviations in the frequency distribution but overall confirm the trend observed in the synthetic data.

Figure 4 presents the shower event relative frequency by day-of-week for the measured and synthetic residence hall data. The patterns indicate higher shower frequencies on weekdays, with peaks on Wednesdays and Fridays. This consistency between the measured and synthetic datasets confirms the robustness of our synthetic data and supports further use for comparative analysis with the REU data. The relative frequencies show that both datasets have similar distributions, with the synthetic data closely following the trend of the measured data.

4.3. Comparative analysis of residence hall data and REU data

4.3.1. Shower duration distribution

Figure 5 shows the shower duration frequency for the synthetic residence hall and REU data. The synthetic residence hall data exhibit a higher mean duration (9.59 min) compared to the REU data (7.02 min), representing a practical difference (based on medium effect size from Cohen's *d*; see SI for additional details). The standard deviation in the synthetic residence hall data is also greater (6.45 min compared to 4.79 min),

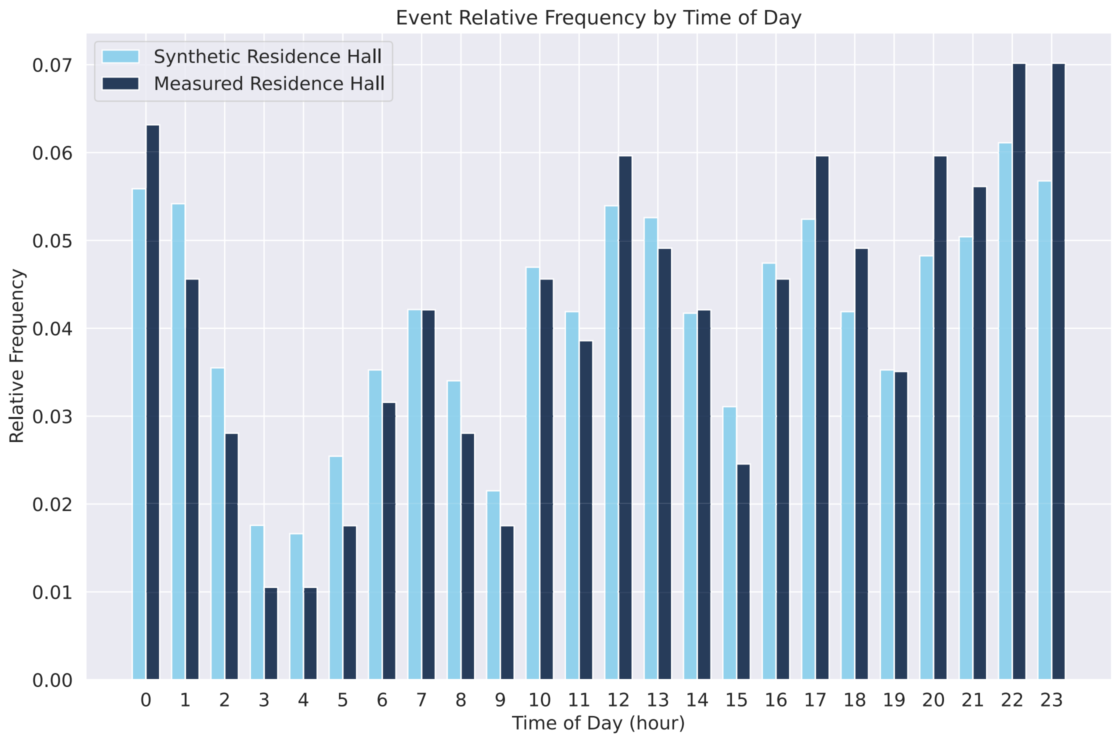

Figure 3. Shower event relative frequency by time-of-day for measured and synthetic residence hall data.

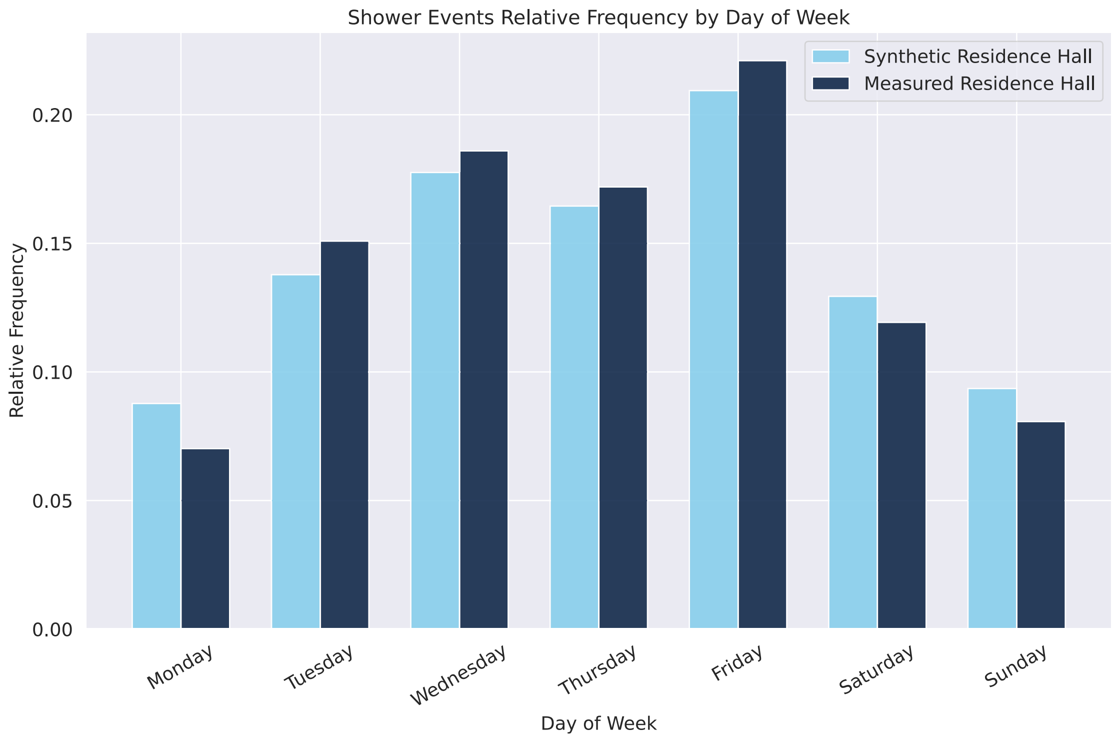

Figure 4. Shower event relative frequency by day-of-week for measured and synthetic residence hall data.

indicating a wider range of shower durations among university students. These results suggest that students' shower habits are more variable, likely due to flexible schedules and the communal living environment, which can influence shower duration. Our analysis also identified 28 events exceeding 16.5 min, representing the 90th percentile in shower duration, which were more frequent at the end of the week, particularly on Fridays.

The shower duration distributions for the synthetic residence hall and REU data have practical differences between the tails. The synthetic residence hall data contain more short-duration events (0–2 min)

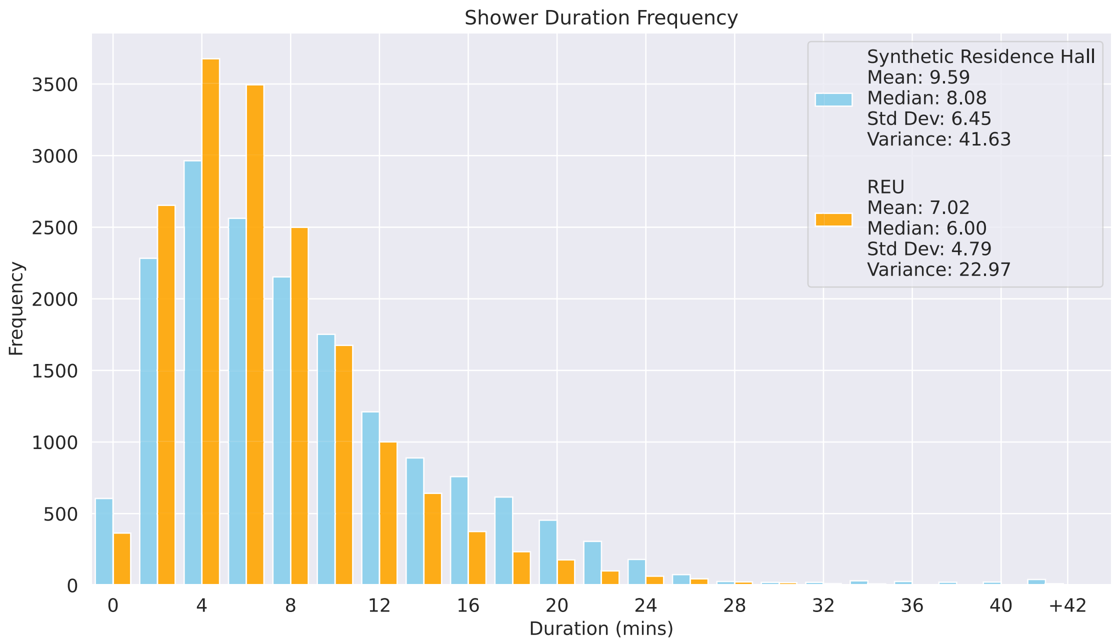

Figure 5. Shower duration frequency for synthetic residence hall and Residential End Uses of Water (REU) data.

at a frequency higher than the REU data. These short-duration events might be attributed to quick rinses, cleaning of the shower, or other brief activities. In addition to students' quick showers, PAR's building maintenance schedule reported daily cleaning of the showers, during which short-term shower 'events' could occur. Conversely, the REU data show fewer of these short events. On the other hand, the synthetic residence hall data contain more long-duration events, indicating some students take extended showers. These tail events highlight event variability and the need for tailored water conservation strategies in university settings.

Despite the differences at the tails of the distributions, the overall shape of the distributions between these extremes is quite similar for both datasets. This similarity suggests that, aside from the extreme events, shower durations in university student housing and U.S. single-family households follow comparable distributions, with a majority of showers falling within a similar range.

4.3.2. Time-of-day patterns for shower events

The event count by time-of-day for the synthetic residence hall and REU data is depicted in figure 6. The synthetic residence hall data show events throughout the day with moderate peaks at 12:00 PM, 5:00 PM, and 10:00 PM, reflecting the unique schedules of university students. In contrast, the REU data show more consistent peaks in the morning (7:00–8:00 AM) and evening (7:00–8:00 PM), corresponding to typical work and school routines.

The late-night peak in the synthetic residence hall data highlights the different lifestyle and activity patterns of university students compared to U.S. single-family households. This late-night peak might reflect students' irregular schedules, late-night studying, and social activities that extend into the night. Unlike single-family households, where shower times are more regular, university students have more flexible routines that allow for greater variability in daily activities, including showering.

The patterns of spread-out shower event times in the residence hall data suggest that students might be showering whenever possible, rather than at specific times of the day, as is more common in households. This variability in shower times underscores the need for flexible and adaptive water conservation strategies tailored to the unique habits of university students. For instance, real-time feedback mechanisms could be implemented to remind students of water conservation practices, regardless of the time-of-day they choose to shower.

4.3.3. Day-of-week patterns of shower events

Figure 7 illustrates the shower events by day-of-week for the synthetic residence hall and REU data. The synthetic residence hall data indicate higher shower frequencies on Fridays, suggesting increased water usage as students prepare for weekend activities. This trend is consistent with the observed peak on Fridays in the measured residence hall data (see figure 4).

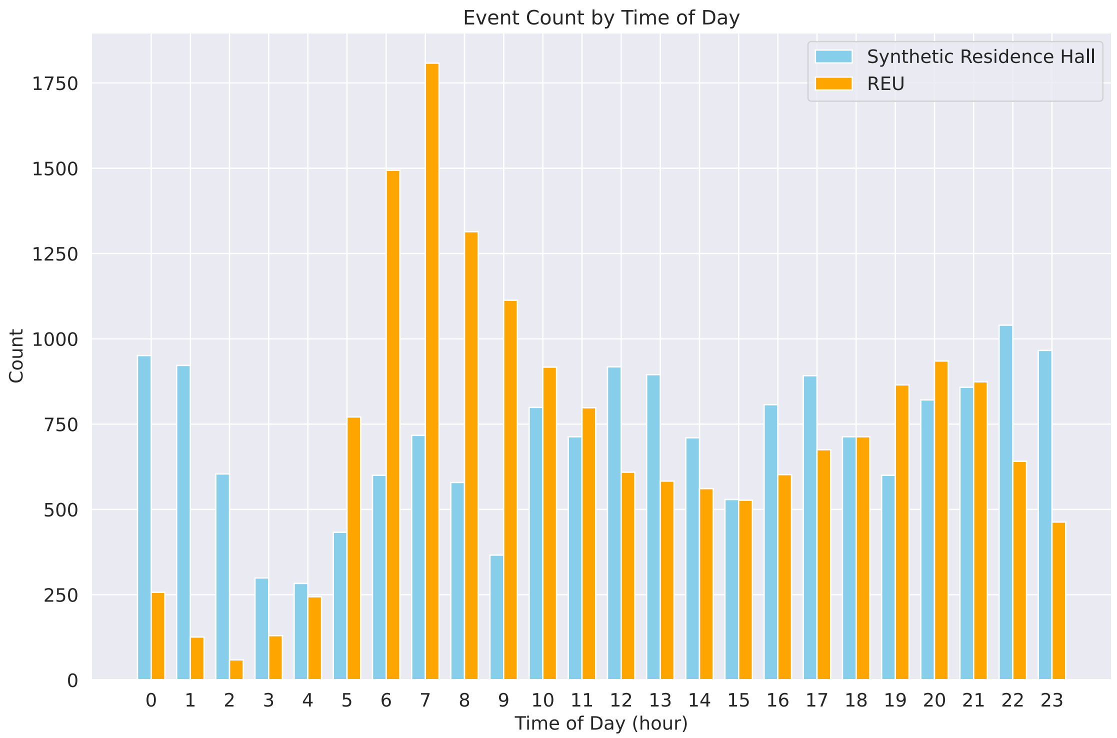

Figure 6. Shower event count by time-of-day for synthetic residence hall and Residential End Uses of Water (REU) data.

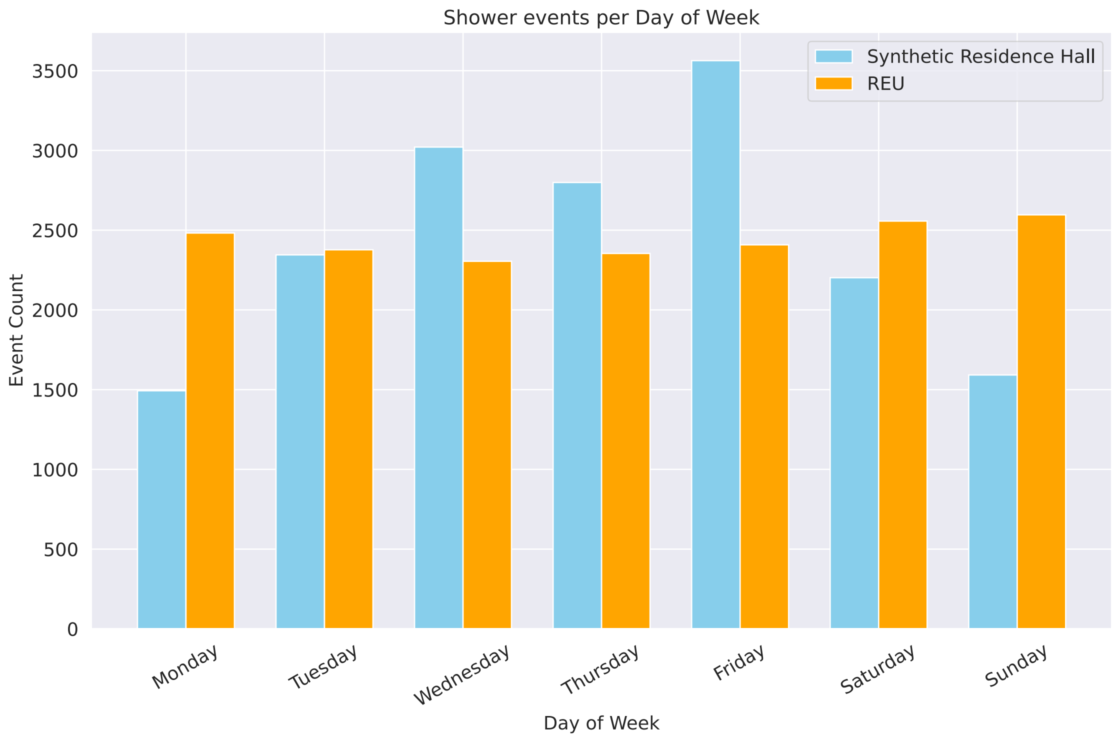

Figure 7. Shower events by day-of-week for synthetic residence hall and Residential End Uses of Water (REU) data.

In contrast, the REU data show a more uniform distribution of shower events throughout the week, corresponding to the regular schedules of single-family household residents. The synthetic residence hall data also show a notable decrease in shower events over the weekend, potentially due to students leaving campus or having less structured schedules on these days.

Major shower events, defined as those exceeding 16.5 min (90th percentile in residence hall shower duration), were predominantly observed on Thursdays and Fridays. This pattern aligns with the overall event count distribution, where the majority of shower events occur from Wednesday to Friday. These major events could reflect students' preparations for weekend activities and social events, further emphasizing the peak usage periods. The SI (table S1) provides a detailed breakdown of major events by day-of-week.

5. Broader implications

5.1. Data uncertainty and limitations

Our primary data collection through shower water metering fills a notable gap in indoor water data at specific end uses for a unique population. However, these data present uncertainties and limitations around human behaviors and end-use data collection that can shape future research directions.

Water use during a shower event is determined by both infrastructure (i.e. showerhead flow rate) and user behavior (i.e. duration, frequency). This intersection of humans and infrastructure constitutes a complex sociotechnical system [75, 76], with interdependent decision-making and consumption such that change comes from many individuals separately and collaborative social behavior [77]. Variability in shower duration is significant, with right-skewed distributions of shower duration observed in single-family residential households [6] and our data for university student housing (see figure 2). Specific in-shower behaviors such as hygiene habits are not captured by end-use water metering alone. Survey data, water diaries, and focus groups can reveal additional information about showering behaviors, but can also present gender bias and other privacy challenges [78, 79].

One notable limitation is the duration and timing of the data collection. The observed data were collected during periods of occupancy while classes and exams were in session, excluding breaks and holiday periods from the analysis. While this timeline provides a focused view of showering behavior during typical academic routines, the dataset does not cover a long enough continuous time series to evaluate potential seasonal dynamics, such as differences in water usage between warmer and colder months. Given that academic schedules vary across institutions, additional research across multiple universities would help determine whether seasonal trends in student showering behaviors are consistent across different climates and academic calendars. Future studies with extended time series data could help identify and account for these potential seasonal variations, providing a more comprehensive understanding of the showering behaviors of university students throughout the academic year.

Shower end-use metering presents challenges of non-intrusive continuous data collection. The Pani Smart Water Monitors we used in this study depend on AA alkaline battery power, which is advantageous for non-intrusive, ambient monitoring but limited for long-term, continuous data measurement and recording. Discontinuities in data collection can miss different shower behaviors and habits, such as long-duration events or turning off the water while soaping up, a common water conservation recommendation [78–80]. In our data processing, we consider such instances as single shower events, acknowledging uncertainty in behaviors and habits.

Our synthetic shower data introduce opportunities for further research, with some limitations given uncertainties in the underlying actual data collection. Based on our visual and quantitative analysis, the synthetic residence hall data represent the primary features of the actual (i.e. measured) data well. Our synthetic data strike a balance between adequately reflecting actual conditions and the risk of overfitting. Consequently, the synthetic shower data are not an exact fit or replication of the actual measured data, allowing for statistical variability.

5.2. Population specificity

The unique characteristics of college students in university housing can significantly influence water usage behaviors. Previous studies with limited sample sizes have shown lower average water use among college students compared to city-wide average per capita water use, likely due to limited outdoor water use among student populations [78, 81]. In a limited sample of U.S. college students, occupants expressed opinions that most of their residential water use was for showering [81]. Metered and self-reported water diary data representing U.K. first-year college students showed higher water consumption on weekdays compared to weekends and longer shower durations on average (10–12 min) than the U.K. population norm (7–8 min) [78], similar to our findings for UIUC students. The nature of our population—residents in university student housing—presents specific characteristics of semi-permanent housing that can be notably different from permanent single-family residential housing (e.g. [6]) and impermanent (i.e. temporary) hotel housing (e.g. [45]).

Our measured data represent selected student housing locations at one U.S. university. These data provide useful observations of showers in student housing, but they are not representative of all universities or student housing contexts independently or compared to U.S. single-family residences. Water use behavior can vary in response to different bathroom infrastructure, genders, campus culture, and other factors beyond the scope of this study, representing areas for future work.

5.3. Promoting conservation behaviors

As demonstrated by the Tiefenbeck *et al* study [45] of hotels in Switzerland, effective mechanisms can create a direct connection between consumers and the consequences of their water and energy use in temporary housing settings, even without financial incentives. While the analysis eliminated self-selection bias, the study still represents a specific population (i.e. hotel patrons) and might not be representative of the entire population. Since similar conditions are present in semi-permanent housing in university residence halls and private certified housing, promoting water conservation behaviors in these contexts requires tailored approaches that align with student lifestyles.

Conservation opportunities could begin with targeting long-duration shower events, particularly those exceeding the 90th percentile (16.5 min). Reducing the duration of these extended shower events closer to the population average could significantly reduce overall water usage. Additionally, time-of-day patterns, such as peak usage in the evenings, present another opportunity for intervention, as shifting or shortening peak showers could alleviate resource demand and infrastructure stress.

Effective strategies for promoting water conservation behaviors among university students include education and awareness [82], social influence [83], gamification [84], and convenience [85]. Continuously providing students with information about the environmental and financial benefits of water conservation can affect current usage behaviors and shape future behaviors, especially in a context of financial responsibility for water bills. Peer influence also plays a crucial role; modeling expected behaviors [79] or encouraging students to share their conservation efforts can create a sense of social responsibility [83].

Incorporating gamification elements, such as turning water conservation into a residence hall-wide challenge, can engage students and motivate reduced water use [86]. Providing real-time feedback and water-efficient fixtures can further facilitate these behaviors. Understanding and leveraging personal values, such as the convenience and comfort of having readily available water, can also motivate students to adopt water-saving practices. These strategies can form the foundation of a possible feedback campaign to encourage water conservation as future research.

By focusing on both long-duration events and peak time-of-day usage, conservation strategies can address specific behaviors contributing disproportionately to water consumption. Implementing these strategies, independently or concurrently, at varying scales depending on available resources, can enhance the effectiveness of water conservation efforts in university student housing settings.

6. Conclusion

Through the implementation of end-use water metering of shower events among residents in semi-permanent university student housing contexts, this study contributes to understanding water usage behaviors in comparison to U.S. single-family residential settings. By examining student shower habits in residence halls and private certified housing at the University of Illinois Urbana-Champaign, we demonstrate several key findings and implications.

First, acknowledging measurement and data collection challenges, we expanded our university student housing shower measurements through creation of synthetic residence hall data. We used CTGANs to generate 59 batches of 285 synthetic data points, simulating approximately 17 000 shower events to align with single-family residential shower observations. These synthetic residence hall data accurately reflected the time-of-day, day-of-week, and duration characteristics of the measured university student housing shower events. This synthetic data approach fills a notable gap in available water end-use data.

Second, our assessment of shower event behaviors among UIUC students revealed practical differences compared to U.S. single-family residential settings. In typical residential households, individuals tend to shower daily, usually in the morning with a smaller evening peak [6]. In contrast, residents of university student housing exhibited less regular showering patterns, with longer durations (9.59 min in university student housing compared to 7.02 min in single-family residences), on average, and greater standard deviation (6.45 min compared to 4.79 min). This irregularity in shower habits highlights the unique population context of university students.

Finally, the context of university student housing as a semi-permanent residence presents a unique sociotechnical systems challenge for encouraging water conservation. The atypical behaviors and temporal patterns of university student showers compared to single-family residential showers motivates tailored water conservation strategies. Such targeted interventions, like education and awareness, social influence, gamification, and convenience, could encourage water conservation via showers, even in the absence of financial incentives. We recommend a tailored sociotechnical systems approach for encouraging water conservation in showers among university student populations.

In summary, this research contributes to the broader discourse on end-use water conservation by highlighting the distinct shower water usage behaviors of university students living in semi-permanent housing. By identifying behaviors and patterns and proposing targeted interventions, universities can promote more sustainable water use among student populations. These strategies not only help in conserving a vital resource but can also instill long-lasting conservation habits.

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/.

Acknowledgments

We thank the following individuals for their support in this research: Warren Robinson, University Housing; Paula Hancock and Marc McConney, Presby Hall; Uros Marjanovic, Engineering IT; Allen Tsai, Pani Systems, Inc.; Andrea Cominola, Technische Universität Berlin; and A. Ali Heydari, Google. This work was supported by the Institute for Sustainability, Energy, and Environment and the Student Sustainability Committee at the University of Illinois Urbana-Champaign, and the National Science Foundation, Grant CBET-1847404.

Disclosure

Ashlynn S Stillwell served on the Board of Directors of McKinley Foundation, which owns and operates Presby Hall.

ORCID iDs

Zahra Heydari https://orcid.org/0000-0003-0281-8669
Ashlynn S Stillwell https://orcid.org/0000-0002-6781-6480

References

[1] Shmerling R H 2021 Showering daily — is it necessary? (available at: www.health.harvard.edu/blog/showering-daily-is-it-necessary-2019062617193)

[2] Mayer P W, DeOreo W B, Opitz E M, Kiefer J C, Davis W Y, Dziegielewski B, and Olaf Nelson J 1999 Residential end uses of water *Technical report* American Water Works Association

[3] Hand M, Shove E and Southerton D 2005 Explaining showering: a discussion of the material, conventional and temporal dimensions of practice *Sociol. Res. Online* **10** 101–13

[4] Lutz W and Qiang R 2002 Determinants of human population growth *Phil. Trans. R. Soc. London. Ser.* B **357** 1197–210

[5] Boyle T, Giurco D, Mukheibir P, Liu A, Moy C, White S and Stewart R 2013 Intelligent metering for urban water: a review *Water* **5** 1052–81

[6] DeOreo W B Mayer P W Dziegielewski B and Kiefer J 2016 Residential end uses of water, version 2 Tech. report Water Research Foundation

[7] Gram-Hanssen K 2005 Teenage consumption of cleanliness: how to make it sustainable? *Sustain.: Sci., Pract., Policy* **3** 15–23

[8] Spaargaren G and van Vliet B 2000 Lifestyles, consumption and the environment: the ecological modernization of domestic consumption *Environ. Politics* **9** 50–76

[9] Attari S, Weber E, and Krantz D 2015 Saving energy: personal biases in energy conservation (available at: http://cred.columbia.edu/research/all-projects/saving-energy-ill-do-the-easy-thing-you-do-the-hard-thing/)

[10] Ulriksen L and Nejrup C 2021 Balancing time — university students' study practices and policy perceptions of time *Sociol. Res. Online* **26** 166–84

[11] Buckley P and Lee P 2021 The impact of extra-curricular activity on the student experience *Act. Learn. High. Educ.* **22** 37–48

[12] Geller E S, Erickson J B and Buttram B A 1983 Attempts to promote residential water conservation with educational, behavioral and engineering strategies *Popul. Environ.* **6** 96–112

[13] Jorgensen B, Graymore M and O'Toole K 2009 Household water use behavior: an integrated model *J. Environ. Manage.* **91** 227–36

[14] Moore G T and Warah R 1983 The effects of the physical environment on student residence hall behavior *J. College Univ. Stud. Housing* **13** 16–23

[15] Gardner G T and Stern P C 2002 *Environmental Problems and Human Behavior* (Pearson Custom Publishing)

[16] Schwartz D, de Bruin W B, Fischhoff B and Lave L 2015 Advertising energy saving programs: the potential environmental cost of emphasizing monetary savings *J. Exp. Psychol. Appl.* **21** 158

[17] Kenney D S, Goemans C, Klein R, Lowrey J and Reidy K 2008 Residential water demand management: lessons from aurora, Colorado *JAWRA J. Am. Water Res. Assoc.* **44** 192–207

[18] Graham P A, Socorro Hurtado S and Gonyea R M 2018 The benefits of living on campus: do residence halls provide distinctive environments of engagement? *J. Stud. Affairs Res. Pract.* **55** 255–69

[19] Chawla N V, Japkowicz N and Kotcz A 2004 Special issue on learning from imbalanced data sets *ACM SIGKDD Explorations Newsl.* **6** 1–6

[20] Goodfellow I, Pouget-Abadie J, Mirza M, Bing X, Warde-Farley D, Ozair S, Courville A and Bengio Y 2014 Generative adversarial nets *Advances in Neural Information Processing Systems* vol 27 pp 2672–80
[21] Renzetti S and Dupont D P 2003 *The Value of Water in Manufacturing* (CSERGE)
[22] National Integrated Drought Information System 2024 National current conditions (available at: www.drought.gov/current-conditions)
[23] Hubacek K, Guan D, Barrett J and Wiedmann T 2009 Environmental implications of urbanization and lifestyle change in China: ecological and water footprints *J. Clean. Prod.* **17** 1241–8
[24] Veolia 2020 Suez Survey finds majority of Americans agree water scarcity is a major concern (available at: www.watertechnologies.com/about-us/newsroom/suez-survey-finds-majority-americans-agree-water-scarcity-major-c oncern)
[25] United States Congress 1992 Energy policy act of 1992 (available at: www.congress.gov/102/statute/STATUTE-106/STATUTE-106-Pg2776.pdf)
[26] United States Congress 2005 Energy policy act of 2005 (available at: www.congress.gov/109/plaws/publ58/PLAW-109publ58.pdf)
[27] Environmental Protection Agency 2022 Water sense statistics and facts (available at: www.epa.gov/watersense/statistics-and-facts)
[28] Aitken C K, McMahon T A, Wearing A J and Finlayson B L 1994 Residential water use: predicting and reducing consumption *J. Appl. Soc. Psychol.* **24** 136–58
[29] Willis R M 2011 *Domestic Water end use Study: an Investigation of the Water Savings Attributed to Demand Management Strategies and Dual Reticulated Recycled Water Systems* (Griffith University)
[30] Research Center P 2023 Americans' views of climate change in 8 charts (available at: www.pewresearch.org/fact-tank/2023/03/28/americans-views-of-climate-change-in-8-char ts/)
[31] Research Center P 2023 Majorities of Americans prioritize renewable energy, back steps to address climate change (available at: www.pewresearch.org/fact-tank/2023/06/15/majorities-of-americans-prioritize-renewable-energy-back-steps-to-address-climate-change/)
[32] UN Water 2023 Water and climate change (available at: www.unwater.org/water-facts/climate-change/)
[33] Chini C M, Schreiber K L, Barker Z A and Stillwell A S 2016 Quantifying energy and water savings in the U.S. residential sector *Environ. Sci. Technol.* **50** 9003–12
[34] Sønderlund A L, Smith J R, Hutton C J, Kapelan Z and Savic D 2016 Effectiveness of smart meter-based consumption feedback in curbing household water use: knowns and unknowns *J. Water Res. Plan. Manage.* **142** 04016060
[35] Sofoulis Z 2005 Big water, everyday water: a sociotechnical perspective *Continuum* **19** 445–63
[36] Violette D and Ozog M 1989 Correction for self-selection Bias: theory and application *Energy Program Evaluation: Conservation and Resource Management Conf.* (*Argonne, ILArgonne National Laboratory*) pp 241–50
[37] Alarie S and Lupien S J 2021 Self-selection bias in human stress research: a systematic review *Psychoneuroendocrinology* **131** 105514
[38] Jones S R G 1992 Was there a Hawthorne effect? *Am. J. Sociol.* **98** 451–68
[39] Gregersen T, Doran R, Böhm G, Tvinnereim E and Poortinga W 2020 Political orientation moderates the relationship between climate change beliefs and worry about climate change *Front. Psychol.* **11** 1573
[40] Zangheri P, Serrenho T and Bertoldi P 2019 Energy savings from feedback systems: a meta-studies' review *Energies* **12** 3788
[41] Darby S 2006 The effectiveness of feedback on energy consumption: a review for DEFRA of the literature on metering, billing and direct displays *Technical report* Environmental Change Institute, University of Oxford
[42] Lott C J 2017 *The Effect of Financial and Social Incentives on Water Conservation* (University of California)
[43] McCain A 2022 25 hotel industry statistics [2022]: hospitality trends and market data (available at: https://www.zippia.com/advice/hotel-industry-statistics/#:∼:text=Here%20are%20the%20key%20statistics,%243.952%20trillion%20as%20of%202021)
[44] Schons Arenhart R, Mendonça Souza A and Ruviaro Zanini R 2022 Energy use and its key factors in hotel chains *Sustainability* **14** 8239
[45] Tiefenbeck V, Wörner A, Schöb S, Fleisch E and Staake T 2019 Real-time feedback promotes energy conservation in the absence of volunteer selection bias and monetary incentives *Nat. Energy* **4** 35–41
[46] Mary E L and Dennis O F 2016 The social context of energy use *Soc. Issues Policy Rev.* **10** 119–56
[47] University of Illinois Urbana-Champaign 2024 Article 2, Part 2 — Housing Policies (available at: https://studentcode.illinois.edu/article2/part2/2-201/)
[48] Bramwell B and Lane B 2000 *Tourism Collaboration and Partnerships: Politics, Practice and Sustainability* (Channel View Publications)
[49] Rahimi S 2015 Social interaction in student residence halls: an architectural perspective *Master's Thesis* The Pennsylvania State University
[50] Morganti A, Brambilla A, Aguglia A, Amerio A, Miletto N, Parodi N'o, Porcelli C, Odone A, Costanza A and Signorelli C 2022 Effect of housing quality on the mental health of university students during the COVID-19 lockdown *Int. J. Environ. Res. Public Health* **19** 2918
[51] Cedeno Laurent J G, Allen J G, McNeely E, Dominici F and Spengler J D 2020 Influence of the residential environment on undergraduate students' health *J. Exposure Sci. Environ. Epidemiol.* **30** 320–7
[52] Jihun O and Kim J 2021 Relationship between mental health and house sharing: evidence from seoul *Int. J. Environ. Res. Public Health* **18** 2495
[53] Worsley J D, Harrison P and Corcoran R 2021 The role of accommodation environments in student mental health and wellbeing *BMC Public Health* **21** 1–15
[54] Stewart V, Judd C and Wheeler A J 2022 Practitioners' experiences of deteriorating personal hygiene standards in people living with depression in Australia: a qualitative study *Health Soc. Care Commun.* **30** 1589–98
[55] Bialecki T Burns D Charles R Kathan D Lee P Peirovi S, Tita M, and Yaya H 2022 Assessment of demand response and advanced metering *Technical report* Federal Energy Regulatory Commission
[56] Mazzoni F *et al* 2023 Investigating the characteristics of residential end uses of water: a worldwide review *Water Res.* **230** 119500
[57] Koech R, Cardell-Oliver R and Syme G 2021 Smart water metering: adoption, regulatory and social considerations *Australas. J. Water Res.* **25** 173–82
[58] Heydari Z, Cominola A and Stillwell A S 2022 Is smart water meter temporal resolution a limiting factor to residential water end-use classification? a quantitative experimental analysis *Environ. Res. Infrastruct. Sustain.* **2** 045004
[59] Ham J and Midden C 2010 Ambient persuasive technology needs little cognitive effort: the differential effects of cognitive load on lighting feedback versus factual feedback *Int. Conf. on Persuasive Technology* (Springer) pp 132–42
[60] Hermsen S, Frost J, Jan Renes R and Kerkhof P 2016 Using feedback through digital technology to disrupt and change habitual behavior: a critical review of current literature *Comput. Hum. Behav.* **57** 61–74

[61] Vivek V, Malghan D and Mukherjee K 2021 Toward achieving persistent behavior change in household water conservation *Proc. Natl Acad. Sci.* 118 e2023014118
[62] Private Certified Housing. PCH rates (available at: https://certified.housing.illinois.edu/pch-resources/rates/)
[63] University Housing. Intersections (available at: https://housing.illinois.edu/Living-Options/Living-Learning-Communities/Intersections)
[64] University Housing Global crossroads (available at: https://housing.illinois.edu/Living-Options/Living-Learning-Communities/Global-Crossroads)
[65] Presby Hall 2019 FAQ: residents, students & parents interested in Presby Hall (available at: https://presbyhall.com/faq/)
[66] Cominola A, Giuliani M, Castelletti A, Rosenberg D E and Abdallah A M 2018 Implications of data sampling resolution on water use simulation, end-use disaggregation and demand management *Environ. Modelling Softw.* **102** 199–212
[67] Di Mauro A, Di Nardo A, Francesco Santonastaso G and Venticinque S 2020 Development of an IoT system for the generation of a database of residential water end-use consumption time series *Environmental Sciences Proc.* vol 2
[68] Button K S, Ioannidis J P A, Mokrysz C, Nosek B A, Flint J, Robinson E S J and Munafò M R 2013 Power failure: why small sample size undermines the reliability of neuroscience *Nat. Rev. Neurosci.* **14** 365–76
[69] Lei X, Skoularidou M, Cuesta-Infante A and Veeramachaneni K 2019 Modeling tabular data using Conditional GAN *Advances in Neural Information Processing Systems* p 32
[70] Heydari Z and Stillwell A S 2024 Comparative analysis of supervised classification algorithms for residential water end uses *Water Resour. Res.* **60** e2023WR036690
[71] Brenninkmeijer B 2023 Table evaluator (available at: https://github.com/Baukebrenninkmeijer/table-evaluator) (Accessed 2 October 2024)
[72] Pedregosa F *et al* 2011 Scikit-learn: machine learning in python *J. Mach. Learn. Res.* **12** 2825–30
[73] Chen T and Guestrin C 2016 XGBoost: a scalable tree boosting system *Proc. 22nd ACM SIGKDD Int. Conf. on Knowledge Discovery and Data Mining* pp 785–94
[74] Robinson M C, Glen R C and Lee A A 2020 Validating the validation: reanalyzing a large-scale comparison of deep learning and machine learning models for bioactivity prediction *J. Comput. Aided Mol. Des.* **34** 717–30
[75] Chappin E J L and van der Lei T 2014 Adaptation of interconnected infrastructures to climate change: a socio-technical systems perspective *Util. Policy* **31** 10–17
[76] Hazell P, Novitzky P and van den Oord S 2023 Socio-technical system analysis of responsible data sharing in water systems as critical infrastructure *Front. Big Data* **5** 1057155
[77] Buehler R, Messervey D and Griffin D 2005 Collaborative planning and prediction: does group discussion affect optimistic biases in time estimation? *Organ. Behav. Hum. Decis. Process.* **97** 47–63
[78] Simpson K, Staddon C and Ward S 2019 Challenges of researching showering routines: from the individual to the socio-material *Urban Sci.* **3** 19
[79] Aronson E and O'Leary M 1982 The relative effectiveness of models and prompts on energy conservation: a field experiment in a shower room *J. Environ. Sys.* **12** 219–24
[80] González-Gómez F, López-Ruiz S and Tortajada C 2022 Promoting water conservation habits in shower use: review of water utility websites in OECD cities *Water Int.* **47** 632–45
[81] Dodson G, Jensen T, Cridebring A, and Lungole M 2013 Analysis of student water use in the city of davis *Technical report* University of California Davis
[82] McMakin A H, Malone E L and Lundgren R E 2002 Motivating residents to conserve energy without financial incentives *Environ. Behav.* **34** 848–63
[83] Steg L 2008 Promoting household energy conservation *Energy Policy* **36** 4449–53
[84] Konstantakopoulos I C, Barkan A R, Shiying H, Veeravalli T, Liu H and Spanos C 2019 A deep learning and gamification approach to improving human-building interaction and energy efficiency in smart infrastructure *Appl. Energy* **237** 810–21
[85] Macchiaroli M, Dolores L, Nicodemo L and De Mare G 2021 Energy efficiency in the management of the integrated water service. A case study on the white certificates incentive system *Int. Conf. on Computational Science and Its Applications* (Springer) pp 202–17
[86] Antonio Report S 2023 San Antonio's utilities are gamifying conservation — and it's working (available at: https://sanantonioreport.org/san-antonio-cps-energy-saws-gamifying-conservation-working/)