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Cost-related notifications in smart homes: influencing resident behavior and shifting peak-hour power loads☆

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ABSTRACT

Smart home technologies have been deployed to reduce or shift residential energy demand by employing scheduling strategies such as time-of-use electricity pricing. This study evaluates behavioral aspects of users equipped with smart home technologies by incorporating cost-related notifications into multiple smart appliances in real-world settings. Smart thermostats, smart plugs, clothes washers, dryers, and dishwashers were installed in eight households for one year to evaluate changes in user behavior and power load shifting. During this period, three cost-related notification features were introduced: (1) mode choices for thermostat control and associated mode-specific cost and temperature displays, (2) delay nudges that encouraged users to postpone appliance use during peak periods by showing potential savings, and (3) monetary incentives for deferred operation. Results revealed that mode-specific cost information led users to make clear trade-offs between cooling preferences and monetary cost. Users were willing to pay an additional dollar to lower the thermostat setpoint by 0.72°F during the summer months. The delay nudges resulted in 82% of appliance cycles occurring off-peak, shifting washers and dishwashers and reducing their peak-hour loads, while dryers achieved measurable savings for users who frequently delayed use. The monetary incentives were also effective, with a one-dollar increase raising delay acceptance by 32% for washers, 25% for dryers, and 46% for dishwashers. These findings highlight the importance of refining notification intensity and design to match each appliance's demand profile and intended behavior. By combining cost-related feedback with targeted interventions, smart home systems can reduce peak-period demand and support sustained energy savings.

1. Introduction

A smart home refers to a residence equipped with a communication network that connects various devices, such as sensors, appliances, and control systems, enabling remote monitoring and management [1]. With technology becoming increasingly embedded in daily life, these smart devices, including thermostats, security cameras, and voice-activated speakers, are being rapidly adopted to enhance convenience, home security [2], safety [3], and energy efficiency [4,5]. Reflecting this trend, the global smart home market was valued at USD 127.80 billion in 2024 and is projected to reach USD 537.27 billion by 2030, representing an average annual growth rate of 27.0% from 2025 to 2030 [6]. As of 2025, smart speakers, security cameras, and smart lighting systems are the most widely adopted smart devices, with adoption rates of 19%, 23%, and 26%, respectively. Additionally, 28% of households have integrated smart appliances such as refrigerators, dishwashers, and dryers [7].

One of the main advantages of smart home technologies is their ability to enhance energy efficiency and demand flexibility through methods such as real-time energy monitoring, which is now widely adopted in households [8,9], through IoT-based monitoring and automated controls [10], real-time feedback that guides user decision-making [11], and behavior-shaping smart home interactions [12]. This advantage has been supported by experimental studies demonstrating measurable improvements in household energy efficiency. For example, Malysheva et al. [13] reported that smart washing machines equipped with load optimization functions achieved a 15% reduction in

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energy consumption when operated in energy-efficient mode. Smart dishwashers also demonstrated improved energy and water efficiency under similar conditions. Furthermore, smart thermostats were found to reduce energy use without compromising comfort by lowering indoor temperatures by approximately 1°C during unoccupied periods, based on weather and occupancy data.

While these technologies improve efficiency at the device and user-interaction level, a complementary line of research focuses on how strategic planning and scheduling of appliance operation can further amplify these gains. Planning and scheduling appliance usage can improve demand flexibility by shifting energy-intensive tasks to lower-cost or lower-demand periods through TOU pricing signals [14], coordinating appliance operation with renewable generation and storage to reduce reliance on the grid [15–17], and optimizing load distribution to lower peak demand and overall energy use [16–18]. Several studies have explored strategies within smart home systems to address this issue. Rocha et al. [19] introduced a demand planning method that schedules appliance usage by taking into account electricity price fluctuations, device priorities, operational cycles, and battery storage availability. Their system resulted in a 51.4% reduction in energy consumption and lowered electricity costs for consumers. Similarly, Ma et al. [20] developed an optimization-based scheduling strategy that classifies appliances into those with flexible start times and those with adjustable power levels, enabling a trade-off between electricity cost and user discomfort. Simulation results confirmed the method's effectiveness in reducing payments while preserving comfort. Li and Dong [21] proposed a real-time algorithm for jointly managing load scheduling and energy storage in households with integrated renewable energy, demonstrating that their approach could minimize overall system costs even under uncertain electricity prices and load dynamics. Building on this line of work, recent studies have focused on developing optimization models that reduce electricity bills by shifting appliance operation to lower-cost time periods rather than shifting tariff structures themselves. For instance, Ikram et al. [22] employed optimization techniques to reschedule shiftable loads during cost-effective hours while minimizing the peak-to-average ratio in a smart home equipped with rooftop solar panels, a battery, and an inverter. Simulations demonstrated that these strategies effectively reduced electricity costs by 4.5%, with the optimized schedules producing performance levels similar to more computationally complex algorithms, indicating comparable outcomes under practical conditions.

Alongside these technological innovations, recent studies have explored how nudging techniques can enhance energy saving and promote behavioral change in residential and digital environments [23–25]. Building on this growing body of work, researchers have proposed a range of behavioral approaches designed to support more sustainable household practices. Such approaches include smartphone and web-based prompts that encourage energy-saving actions [26], choice architecture that guides users toward welfare-enhancing energy plans [27], and motivational interventions with interactive feedback that reduce household electricity and water use [28]. Nudging is a behavioral science approach that aims to steer individuals toward beneficial choices without restricting their freedom or altering their economic motivations significantly [29]. In digital contexts, digital nudging refers to the design of user interfaces in information systems that leverage cognitive biases to guide user behavior toward desirable outcomes while preserving user autonomy [30]. To assess the effectiveness of such nudging techniques, several empirical studies have implemented them in residential settings. For instance, Hirayama et al. [31] found that combining a nudge-based energy-saving app with a home energy management system resulted in a 3.5% reduction in winter energy consumption, compared to a 2.4% reduction with the app alone. Similarly, Kim et al. [32] demonstrated that delivering personalized energy efficiency advice based on electricity usage data and nudging principles resulted in a statistically significant 1.3% reduction in electricity consumption. Additionally, Wang et al. [33] found that real-time and historical electricity usage feedback led to an average 7.1% reduction in household energy consumption. Sudarshan [34] conducted a field experiment to examine how households respond to different behavioral interventions, including weekly reports comparing electricity use with peers, the same reports supplemented with monetary incentives, and natural variation in electricity prices. The study found that peer comparison nudges alone reduced summer electricity consumption by 7%, an effect comparable to a 12.5% increase in tariffs. Bird and Legault [35] highlighted that the effectiveness of interventions varies greatly depending on the decision structures and how different strategies are combined. They noted that interventions tend to be more successful when they integrate feedback, motivation, and active engagement with clear and consistent communication.

Although prior work has examined nudges for energy conservation, little is known about how cost-related notifications embedded directly into appliance interfaces influence real-time behavioral decisions and power load shifting. Embedding notifications at the point of use is particularly important because it delivers feedback precisely when decisions are made, which can increase acceptance and support autonomy. Research on how TOU pricing and peak-hour avoidance strategies interact with such notifications remains limited, and it is unclear whether different appliances respond differently to these interventions. These gaps matter because appliance-integrated notifications may reduce peak demand more effectively than standalone messages by aligning feedback with users' immediate choices.

This study investigates how cost-related notifications, including information-based nudges and monetary incentives, affect both resident behavior changes and load shifting when delivered directly through smart appliances. It also examines which types of notifications and which appliance contexts are most effective in promoting energy-saving behavior. The following research questions guide this study:

1) How does mode-specific cost and temperature information displayed on thermostats influence users' behavior?
2) Can cost-saving nudges that inform users about the benefits of delaying appliance usage, specifically for dishwashers, washers, and dryers, effectively influence resident behavior and reduce peak-hour demand?
3) Do monetary incentives for delaying appliance usage lead to measurable changes in user behavior, and how do these effects vary across different appliance types?

To address these questions, this study conducts a long-term field experiment to examine how cost-related notifications influence both users' behavior and household energy demand in real-world smart home environments. By analyzing how residents respond to different types of information and incentives during everyday appliance use, this study offers practical insights into how smart home systems can better support energy-saving and/or cost-saving decision making. The findings are intended to guide the development of more effective energy-saving features for future smart home technologies by demonstrating how well-designed notifications can help shift usage away from peak hours, reduce demand on the grid, and create more balanced and sustainable load profiles.

2. Methods

2.1. Smart home features and field study measurements

To evaluate its real-world performance, the field study was conducted using a residential testbed where EnergyKit was installed and assessed for its connectivity and communication with smart appliances, electrical performance, and user feedback across eight homes. EnergyKit is a pre-commercial home energy management system (HEMS) developed by Ynventive. Three distinct cost-related notification features were implemented through the system, each introduced at different times and across different households during the study period. These features included: (1) mode-specific cost and temperature display for thermostat control, (2) cost-saving informational nudges encouraging users to delay appliance use during peak periods, and (3) monetary incentives offering small financial rewards for delayed usage. Feature 1 was applied to air conditioning systems, while the second and third features targeted clothes washers, clothes dryers, and dishwashers. Features 2 and 3 were applied sequentially to the same appliances, whereas Feature 1 was implemented only during the summer period. In addition, the features 1 and 3 were designed primarily to influence user behavior, as they encouraged users to make cost-aware choices regardless of whether their actions occurred during peak or off-peak periods. In contrast, the feature 2 explicitly incorporated peak-period pricing information by informing users how much they could save by delaying appliance operation, thereby targeting both behavior change and power load shifting.

The field study component of the analysis provided real-world power consumption of appliances and nudge acceptance rates, defined as the proportion of notifications that resulted in the user choosing the suggested action, for each EnergyKit feature deployed in eight single-family homes in the Sacramento Municipal Utility District (SMUD) territory from November 2023 to September 2024. To ensure that the effects of each feature could be evaluated independently, the interventions were deployed in non-overlapping periods. The feature 1 (06/01/2024–09/30/2024) focused on thermostat cost information, the feature 2 (11/08/2023–03/13/2024) provided cost-saving nudges for appliances, and the feature 3 (03/26/2024–09/30/2024) introduced monetary incentives. By exposing households to only one feature during each period, the study isolated users' responses without confounding interactions among features. Fig. 1 provides an overview of how each smart feature is applied to different appliance types and highlights whether the feature is intended to influence user behavior change or power load shifting. The power consumption of plug-in appliances was measured using the YoLink device [36,37], which captures outlet-level energy use. A thermostat, clothes washer, clothes dryer, and dishwasher were provided and installed in each household as part of the field study setup. The specifications and data collection details for other appliances are summarized in Table 1.

Table 1
Specifications and sampling intervals of devices used in the field study.

Controller / Appliance Type	Manufacturer	Model	Sampling interval
Screen / Speaker	Amazon	EchoShow 5	Every 0.5 s
Plug Load	YoLink	YS6602-UC	Every 1 min
Thermostat	YoLink	YS4003-UC	Variable; minimum 1 min
Clothes Washer	GE	GFW650SSNWW	Event-based (button press) or 0.02 s
Clothes Dryer	GE	GFD65ESSNWW	
Dishwasher	GE	PDT785SYNF	

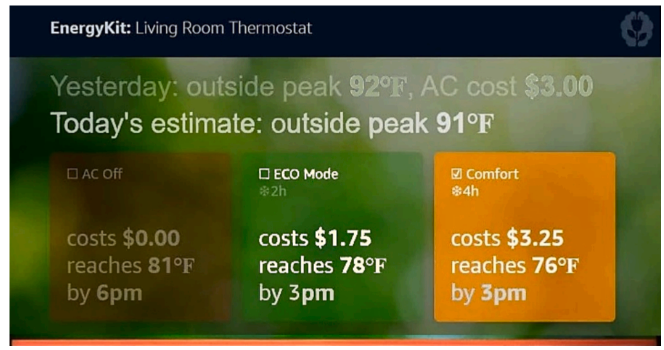

Fig. 2. Thermostat interface displaying estimated cost and target temperature for Eco and Comfort modes.

2.1.1. Mode-specific cost and temperature estimates for thermostat

The thermostat mode selection feature, accompanied by a mode-specific cost estimate display, was deployed across all eight homes during the summer period, from June 1 to September 30, 2024, offering homeowners a new way to control their air conditioning. Users could choose between three options: Off Mode, Eco Mode, and Comfort Mode. Each mode displays estimated operation costs, set temperature, and the duration of the operation (Fig. 2). For Eco Mode and Comfort Mode, estimated runtime of the HVAC system is also displayed. Comfort mode allows for a lower target temperature setting than eco mode, resulting in a cooler indoor environment but at a higher estimated cost. The display also included the forecasted peak outdoor temperature for the day. The target temperature and corresponding estimated cost for each mode were preconfigured and displayed on the thermostat in real-time. On average, across all thermostat interaction events recorded in participating households, the target temperature for Comfort mode was 76.8°F (SD = 2.55), while Eco mode had a slightly higher average of 78.3°F (SD = 2.46), resulting in a mean difference of 1.54°F (SD = 1.03) between the two settings. In terms of estimated cost, Comfort mode averaged \$4.31 (SD = 2.50), whereas Eco mode averaged \$3.34 (SD = 2.48), with a mean difference of \$0.97 (SD = 0.92). These values represent system-generated estimated costs displayed on the interface at the time of mode selection, based on the anticipated operation duration for each option. Users were expected to make their selection based on the displayed pricing information and the target temperature associated with each mode. This setup enabled the analysis of user decision-making patterns based on the estimated cost and temperature information displayed at the time of selection, particularly in the context of selecting between Eco and Comfort modes under varying cost conditions. Corresponding power loads for each selected mode were also measured (Fig. 3).

2.1.2. Cost-saving nudges for delaying washer, dryer, and dishwasher usage

The delay nudge system for clothes washers, clothes dryers, and dishwashers provided homeowners with cost-related nudges that conveyed the current operating cost of the appliance and how much could be saved by postponing usage to off-peak hours. The off-peak period was defined based on SMUD's TOU electricity rate structure, where peak hours were set from 5:00 to 8:00 PM. SMUD's experience with TOU rates showed that most customers stayed on the rate and modestly shifted their energy use [38], suggesting that additional prompts in the home could encourage even greater response. An

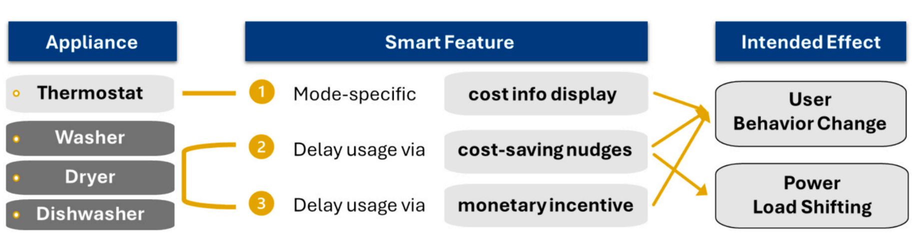

Fig. 1. Overview of appliance-specific smart features, with the features 1 and 3 focused on user behavior change, while the feature 2 addressed both user behavior change and power load shifting.

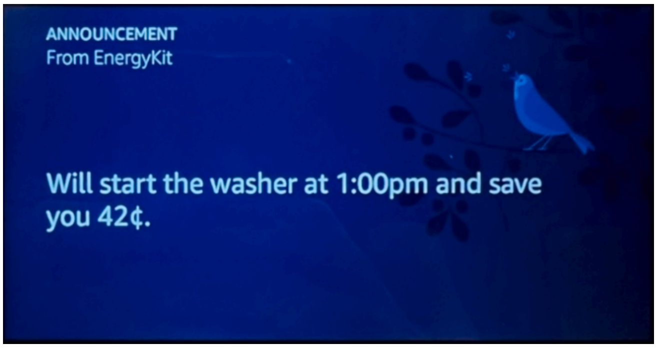

Fig. 3. Cost-saving nudges interface displaying delayed appliance start time and estimated savings.

Amazon EchoShow device was placed near each appliance to deliver both audio and visual messages. These nudges were designed to guide user decisions by showing the potential savings from shifting appliance use outside of peak pricing windows. The displayed price information was derived from a pre-loaded rate table that reflected SMUD's TOU pricing scheme. To act on these nudges, users interacted with a delay button on the appliance, which allowed them to select a later start time for the cycle. Once a time was chosen, EnergyKit scheduled the appliance to run at the selected time without requiring further user input.

Users encountered one of four possible usage scenarios:

1) No delay, off-peak usage: When a user chose to operate an appliance during off-peak hours, Energykit delivered a positive feedback message via both the EchoShow screen and speaker, encouraging the user that it was a good time to run the appliance. The user would then start the appliance as usual.
2) No delay, on-peak usage: If a user attempted to run the appliance during peak hours (5–8 PM), the device issued a nudge informing them of potential monetary savings realized if they postponed the usage. Despite this, the user proceeded to run the appliance without delay.
3) Delayed usage, off-peak hours: When the user received a delay nudge after attempting to use the appliance during peak hours, pressed the delay button, and set the start time to an off-peak hour (e.g., 11 PM), initiated the cycle without further delay.
4) Delayed usage, on-peak hours: When the user received a delay nudge after attempting to use the appliance during peak hours and selected a delayed start time that overlapped with peak hours (e.g., 7 PM), the system automatically postponed the cycle until the end of the peak period (after 8 PM) and informed the user of the updated start time along with the estimated cost savings associated with the shift.

Among these four scenarios, scenarios 1, 3, and 4 represent cases in which the appliance was ultimately operated during off-peak hours, thereby avoiding peak pricing. In these cases, users received the positive feedback message, "Good. This is a good time to run your appliance." Specifically, scenario 1 reflects natural off-peak usage without any delay setting, while scenarios 3 and 4 involve intentional postponement using the delay function to shift operation away from peak hours. In contrast, scenario 2 is the only case where the appliance was run during the peak period despite the cost-saving nudge. In this situation, the user received the cost-related notification, "You could save $0.45 if you let the appliance start in two hours." The appliances were installed from September 2 to November 7, 2023, during the initial phase without the delay feature. The cost-saving nudge feature was introduced on November 8, 2023, and remained active until March 13, 2024, allowing for a comparison of power load before and after the implementation of the nudge intervention.

2.1.3. Monetary incentives for delaying washer, dryer, and dishwasher usage

The monetary incentive feature was designed to incentivize homeowners to shift the operation of their appliances, specifically dishwashers, clothes washers, and clothes dryers, to a later time by offering monetary rewards. This feature was active continuously, independent of peak-hour pricing, throughout the day and was implemented between March 25 and September 30, 2024. The primary aim of this incentive was to examine user responsiveness to financial incentives and determine the minimum reward necessary to influence behavior. This information helped identify the times when users were most willing to shift their appliance usage and the incentive level required to motivate that change.

When a user first interacted with an appliance, EnergyKit prompted them to delay the cycle by two to four hours and displayed a randomly assigned reward between zero and eight dollars. A message and audio prompt asked, "Can you delay this?", after which the user could either continue normally or choose to delay. If the user accepted, the interface allowed them to select a new start time within the valid delay window, and the corresponding incentive amount was shown on the screen, as illustrated in Fig. 4.

If the user did not confirm a delay and returned later, the system issued a second prompt with an updated delay window that still totaled two to four hours from the original interaction time, while keeping the incentive amount the same. Once the user selected a delayed start time, the appliance was scheduled automatically. For example, if a user interacted at 7 PM and agreed to a two-hour delay, the appliance would begin at 9 PM, and the user would receive the reward. If the user reopened or canceled the appliance before the scheduled start, the system preserved the previous incentive amount and generated a new delay prompt based on the updated interaction

2.2. Field study home selection

Eight single-family homes located in Sacramento were selected as test sites for the field study, as shown in Fig. 5, with recruitment carried out in collaboration with the SMUD. The purpose of selecting these homes was to provide a testbed for evaluating the system's performance, including its ability to reliably connect to appliances and influence energy consumption through automated and behavior-modifying control features. Preference was given to homes with two to five residents to align with typical household sizes in the region, as indicated by the 2019 California Residential Appliance Saturation Study [39], which reported an average of 3.1 residents per single-family home, and the 2017–2022 U.S. Census [40], which reported an average of 2.9 residents per home. Additional considerations included the responsiveness of homeowners, their willingness to participate and sign the Research Use Agreement (RUA), and their overall openness to engaging with new technology. To be eligible for the field study, homeowners and their properties had to

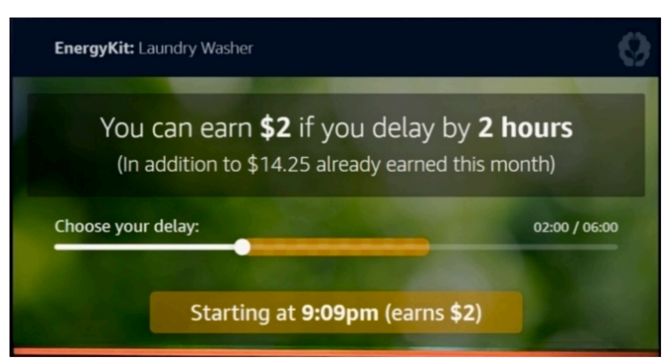

Fig. 4. Incentive interface showing potential monetary reward for delaying usage and a slider bar to select the delay time.

Fig. 5. Field deployment map showing the eight participating homes and their installed smart appliances.

meet several requirements. Participants were required to be SMUD customers, at least 18 years old, and the legal owners of their single-family homes. Eligible homes had to be built between 1992 and 2022 because they generally have better insulation and windows, which help minimize energy loss and make them more suitable for evaluating advanced control approaches. It is found that homes built to the 1992 code or later are approximately 30% more efficient, highlighting the improved performance of newer construction [41,42]. Homeowners agreed to provide basic demographic information, including name, age, phone number, and email, as well as details about their home, such as the year of construction, appliance types, energy sources, internet connectivity, number of residents, and past energy billing information or permission for SMUD to share this data.

Four steps were used to enroll SMUD customers into the field study based on the eligibility requirements. These included an initial email survey, a follow-up call, a home visit, and the execution of a RUA and consent form. First, SMUD sent a survey to 665 eligible customers, asking about their willingness to participate from November 2023 through September 2024, as well as home characteristics, appliance types, energy sources, and household size. A total of 105 customers responded. Second, for homes that met the basic requirements, California Lighting Technology (CLTC) contacted the homeowner to confirm interest and clarify any unclear survey responses. CLTC reached 29 customers whose responses indicated both eligibility and interest. Third, in-person home visits were conducted for 13 of these homes to verify survey information and document appliance manufacturer and model details. Finally, based on these visits, eight homes were selected to participate and were provided with consent forms and the RUA. All participants provided informed consent through the RUA prior to participation, which outlined the study duration, participation requirements, and data collection procedures. CLTC utilized an RUA contract, signed by both the homeowner and UC Davis, to permit CLTC and its contractors to perform work at homes during the study period. Homes that signed the agreements received smart appliances and devices, including a smart thermostat, a clothes washer, a clothes dryer, a dishwasher, and smart power plugs. All eight homes shared key attributes: each had one electrical panel, electric central air-conditioning, and gas central heating. The main characteristics of the participating homes, along with the smart appliances installed for the field study, are summarized in Table 2, and additional details for each home are provided in Table A in Appendix A. The average hourly electrical load profile across the eight households before any smart features were installed (June-September 2023) is illustrated in Fig. 6. Air conditioning was the dominant contributor to peak demand, accounting for up to 52.6% of total household consumption in some homes and exceeding 60% of on-peak usage, particularly between 5 PM and 8 PM. Lighting and miscellaneous plug loads also increased steadily during the evening, while refrigerator and entertainment loads remained consistent throughout the day. Washer, dryer, and dishwasher cycles were concentrated in defined time windows, often late afternoon or evening, which makes these appliances particularly relevant for demand management efforts. Additional details on each household's total and on-peak power load during July, broken down by appliances, are provided in Table B in Appendix A.

2.3. Data analysis

All raw sensor data, including thermostat setpoints, operating modes, minute-by-minute power readings (watts), instantaneous cost estimates (USD), and appliance activation timestamps were ingested into and queried from an InfluxDB time-series database hosted on Amazon Web Services. InfluxDB is an open-source time series database developed by InfluxData, designed to manage heavy loads of writes and queries while efficiently supporting real-time data collection, aggregation, and integration with visualization tools [43]. Next, data were exported from InfluxDB as CSV files, cleaned, and imported into Python. Hypothesis tests were conducted using SciPy, while regression and mixed-effects models were fit with statsmodels and Pingouin. All statistical tests were two-tailed with an α of 0.05, reporting effect sizes as Cohen's d for t-tests and r for nonparametric tests.

2.3.1. Thermostat control using mode-specific cost and temperature estimates

To compare Comfort versus Eco mode, continuous minute-by-minute power readings were collected from eight residential air-conditioner units. For analysis, these readings were aggregated to the hourly level because the intervention targeted broad daily periods, such as morning, afternoon, and evening, rather than minute-to-minute fluctuations. Hourly aggregation provides a stable measure of the typical power associated with each mode while reducing short-term variability unrelated to the behavioral effects of interest. After rounding timestamps to the nearest hour, readings labeled Comfort or Eco were grouped by household, hour, and mode, and averaged to produce one representative value per household per hour for each mode. Normality of paired Comfort-Eco differences at each hour was assessed via the Shapiro-Wilk

Table 2
Home characteristics and smart devices installed for the eight selected homes.

Home	Home characteristics					Installed smart appliances			
	Year	Type	Area (sqft)	Residents	Beds	Thermostat	Dryer	Washer	Dishwasher
1	2001	2-story	2,192	4	4	✔	–	–	–
2	1993	1-story	1,198	1	3	✔	–	–	✔
3	1996	1-story	2,011	2	3	✔	✔	✔	✔
4	2007	2-story	1,187	5	3	✔	✔	✔	✔
5	2018	2-story	1,679	2	3	✔	✔	✔	✔
6	2003	2-story	2,231	5	4	✔	✔	✔	✔
7	2006	2-story	1,722	1	3	✔	✔	–	–
8	1993	1-story	1,385	3	3	✔	✔	✔	✔

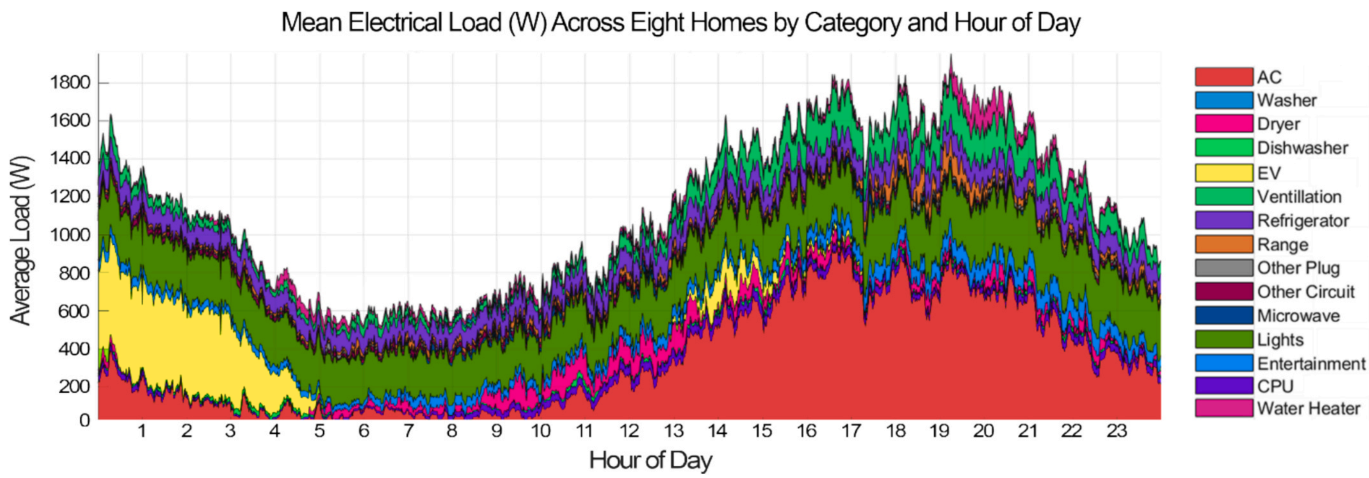

Fig. 6. Mean electrical load (W) across eight homes by category and hour of day from June through September of 2023.

test, and when normality held, paired samples t-tests were applied. When normality was not met, Wilcoxon signed rank tests were used.

Each household's thermostat log, comprising timestamped mode transitions, setpoint (°F), and cost (USD), was chronologically ordered to identify when households switched into Comfort mode and to construct variables that describe the conditions surrounding those decisions. A "Comfort-entry" event was defined as the first record in a continuous block of Comfort mode. This identifies the moment when the user chose Comfort rather than repeatedly counting observations that simply reflect the mode being maintained. For each event, two covariates were computed:

1) Potential savings: Comfort-mode cost minus the contemporaneous Eco-mode cost at the same timestamp, constructed to quantify the financial incentive associated with choosing Eco instead of Comfort.
2) Temperature penalty: Eco-mode setpoint minus Comfort-mode setpoint (°F), which captures how much additional warmth the household would need to tolerate by choosing Eco.

Daily peak outdoor temperature was determined by taking the maximum outdoor reading for each home on each calendar date, and this value was merged into the event dataset. Events were grouped into fifty-cent savings brackets to facilitate comparison of temperature penalties across clearly defined savings levels, and, within each bin, the mean temperature penalty and its standard deviation were computed. This grouping was used to reduce noise in individual observations and to reveal systematic trends in how temperature penalties changed with increasing savings. A Kruskal-Wallis test assessed differences in tolerated warmth across savings brackets, with ε^2 as the nonparametric effect-size measure. To quantify the trade-off continuously, the dependent variable was defined as the temperature penalty for event *i*, and two regression models were estimated:

Model 1 (ordinary least squares, OLS):

$$TemperaturePenalty_i = \beta_0 + \beta_1 PotentialSavings_i + \beta_2 PeakOutsideTemp_i + \varepsilon_i \quad (1)$$

where the subscript *i* indexes an individual Comfort-entry event.

Model 2 (linear mixed-effects model): Same fixed effects as Model 1, plus a random intercept for household to account for baseline differences. Model fit (R^2 or marginal R^2) and parameter estimates (β, SE, *p*-value) are reported for each. Variance of the random intercept is also presented.

2.3.2. Cost-saving nudges for washer, dryer, and dishwasher activations

To evaluate whether cost-saving nudges shifted usage away from peak hours, three outcome measures were constructed: (1) the distribution of activation scenarios, (2) the daily share of appliance load during peak hours, and (3) changes in average appliance-level power consumption. Each measure captures a different behavioral pathway by which nudges may reduce peak demand.

Appliance activations were categorized into "peak-hours avoidance" (Scenario 1: spontaneous avoidance; Scenarios 3–4: deliberate delay via the delay button) and "peak-hours usage" (Scenario 2) to reveal their distribution across peak-hour scenarios. Counts and percentages were tabulated overall and by appliance type. A chi-squared goodness-of-fit test compared the observed avoidance and usage frequencies against an equal-probability expectation.

To measure whether nudges altered when energy was consumed within the day, the hourly load share was computed as each hour's contribution to the total daily appliance load. For each appliance on each day, the hourly load share was defined as:

$$HourlyLoadShare_h = \left(Power_h / \sum_{k=0}^{23} Power_k \right) \times 100 \quad (2)$$

The sum of the shares between 17:00 and 19:59 was defined as the daily peak-hour share (pct_peak). Independent samples t-tests compared the percentage of peak values between the pre-feature and with-feature periods for each appliance. Two retrospective windows (one-month and two-month) were aligned to ensure equal duration and were analyzed separately to assess when effects emerged.

To examine whether households that more consistently avoided peak hours achieved greater reductions in appliance energy demand, households were grouped by their proportion of off-peak activations. This comparison links behavioral responsiveness (avoiding peak hours) with measurable changes in electrical consumption across different appliances. Households were divided into high- and low-avoidance groups based on the median off-peak activation proportions (washer: 0.82, dryer: 0.81, dishwasher: 0.87). For each group, mean power reduction (post-launch minus pre-launch average consumption) was computed. Independent samples t-tests assessed differences in reduction between high- and low-avoidance households; Cohen's *d* is reported as the effect size.

2.3.3. Incentive-based load-shifting acceptance modeling

To assess how monetary offers influenced users' likelihood of delaying appliance cycles, we first computed descriptive acceptance rates for washers, dryers, and dishwashers at each incentive level ($0, $0.50, $1.00, $2.00, $4.00, and $8.00), tabulating counts and proportions to illustrate the dose–response relationship. Next, separate logistic regression models were estimated for each appliance, with acceptance (1 = delay chosen; 0 = no delay) as the dependent variable and offer amount (USD) as the sole predictor. Models were fit by maximum likelihood in statsmodels, using the specification

$$logit(P(accept_i)) = \beta_0 + \beta_1 Offer_i \tag{3}$$

where *logit(p)* denotes the natural logarithm of the odds, defined as log*[p / (1 − p)]*. This transformation maps a probability between zero and one to a continuous scale suitable for regression, and β_1 quantifies how the log-odds of acceptance change with each additional dollar offered.

To test whether the incentive effect differed by appliance, a pooled logistic regression including appliance dummy variables and offer × appliance interaction terms was also fitted, and a likelihood-ratio test compared the full model to one without interactions. Model fit was evaluated using McFadden's pseudo-R2, Akaike information criterion (AIC), and Bayesian information criterion (BIC). Odds ratios (OR = e^β) with 95% confidence intervals were derived via profile likelihood.

3. Results

3.1. Thermostat cost information feature

3.1.1. Mean usage duration and power load (W) between comfort and eco modes

Over the four months, the cumulative usage of Comfort mode across eight households was 8,626 h, while Eco mode was used for a total of 4,404 h. Treating these usage hours as categorical frequency data, a chi-squared goodness-of-fit test revealed a significant difference in the distribution of mode activation time, $\chi^2(1) = 1368.02$, $p < 0.001$. This result indicates that Comfort mode was used for significantly more hours than Eco mode during the study period. On average, households used Comfort mode for 269.6 h per month (SD = 196.1) and Eco mode for 137.6 h per month (SD = 193.5). Considering that each month consists of approximately 720 h (24 h × 30 days), these averages represent 37.4% of the time spent in Comfort mode and 19.1% in Eco mode. The remaining hours correspond to periods when the air conditioning system was in Off mode, and no active cooling was provided.

A paired-samples *t*-test comparing households' mean power consumption across thermostat modes revealed that Comfort mode required significantly more electrical power than Eco mode, as shown in Fig. 7. Across the eight households with complete paired observations, average power usage was 878.60 W in Comfort mode and 496.94 W in Eco mode, $t(7) = 2.82$, $p = 0.026$, with a large effect size ($d = 0.99$). This indicates that, on average, households consistently consumed more power when selecting Comfort mode, even after accounting for between-home variability.

To examine when these differences were most pronounced throughout the day, hourly paired-samples t-tests were conducted using only households that had valid observations for both Comfort and Eco modes within each hour. Daily load patterns showed low power usage during overnight hours, a small rise in the morning, a midday trough, and a substantial increase during late afternoon and early evening. Statistically significant differences between modes appeared at 11 AM, 12 PM, and 8 PM. At 11 AM, Comfort usage (M = 359.12 W) exceeded Eco usage (M = 202.34 W), $t(6) = 2.77$, $p = 0.032$, $d = 1.05$. The difference widened at 12 PM, where Comfort averaged 722.27 W compared with 467.07 W for Eco, $t(4) = 4.31$, $p = 0.013$, $d = 1.93$. A later difference emerged at 8 PM, with Comfort drawing 941.06 W and Eco drawing 654.69 W, $t(4) = 2.98$, $p = 0.041$, $d = 1.33$.

3.1.2. Willingness to trade higher setpoint temperatures for lower energy costs

Each home's thermostat log, comprising timestamped mode, setpoint, and cost readings, was imported and chronologically ordered by household. For each record, the immediately prior operating mode was identified, and a Comfort-mode entry was defined as any record in which the mode switched from non-Comfort to Comfort. To prevent multiple counts during continuous Comfort operation, only the first record of each Comfort interval was retained. For each entry event, two covariates were calculated: 1) potential savings (the difference between the cost of Comfort mode and Eco mode) and 2) temperature penalty (the difference between the target temperature setpoint of Eco mode and Comfort mode). These observations were subsequently binned by savings level and entered into regression models to examine the relationship between temperature penalty and potential savings. This approach quantified the trade-off between cost and comfort by revealing how many degrees Fahrenheit of extra warmth users were willing to accept for each dollar saved.

On average, potential savings were M = 0.97, SD = 0.92 USD, ranging from 0.00 to 5.75 USD. The temperature penalty averaged M = 1.54, SD = 1.03°F, with values ranging from 0.00 to 6.00°F. Daily peak outside temperatures had a mean of M = 99.44, SD = 7.11°F, with a range from 80.70 to 113.90°F. When events were grouped into $0.50 savings increments and the average temperature penalty was plotted, a clear pattern appeared, as shown in Fig. 8. In the smallest savings bracket ($0.00-$0.50, n = 50), users, on average, tolerated just a 0.64°F increase in indoor temperature. As the potential savings grew to $0.50-$1.00 (n = 85), the tolerated increase rose to 1.42°F, and in the $1.00-$1.50 bracket (n = 54), it reached 1.74°F. Those who stood to save between $1.50 and $2.00 (n = 29) accepted a 2.00°F rise. In the most extreme cases, saving $3.50-$4.00, a single user endured a 6.00°F penalty, demonstrating that maximal cost reductions could justify substantial warmth. A Kruskal-Wallis test confirmed that these differences in tolerated warmth across savings levels were highly significant ($H = 86.32$, $p < 0.001$), with savings grouping accounting for approximately one-third of the variance in temperature penalty ($\varepsilon^2 = 0.335$).

The daily peak outside temperature, shown on the thermostat

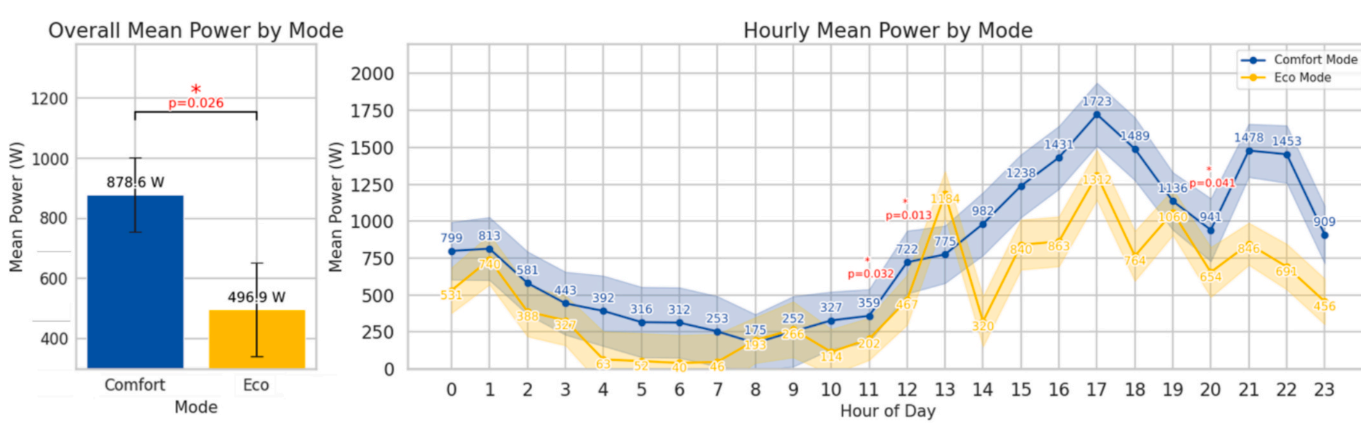

Fig. 7. Mean power load (W) by thermostat mode, showing comfort and eco modes for overall values (left) and by hour of day (right).

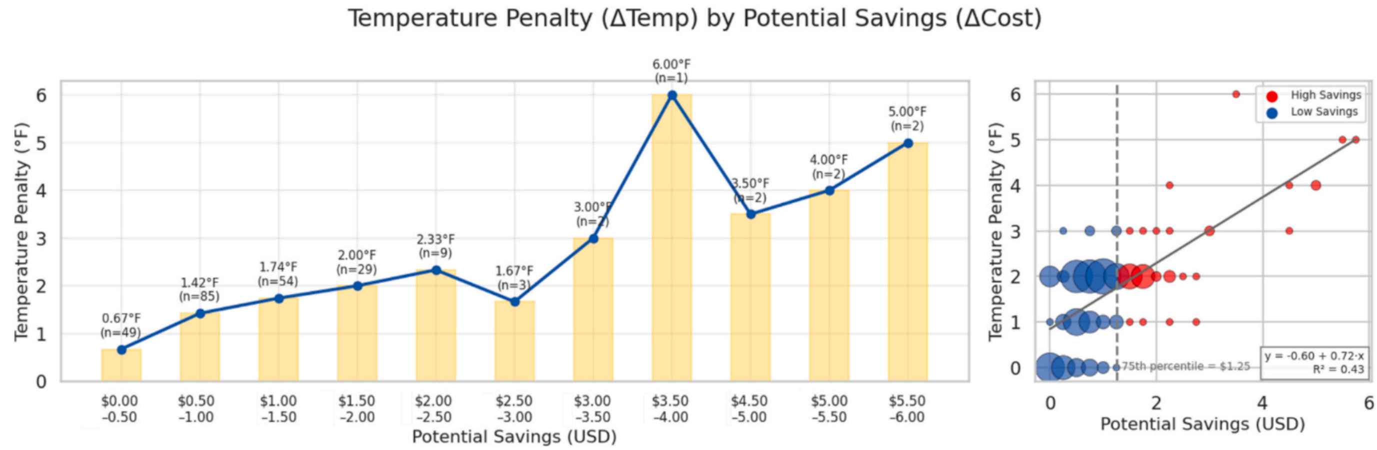

Fig. 8. Temperature penalty (°F) by potential savings (USD) when selecting comfort mode: bin (left) and regression analysis (right).

display, was determined for each home and date by identifying the maximum recorded outdoor temperature and merging this value with the event-level dataset. A fixed-effects ordinary least squares regression was then conducted with temperature penalty as the dependent variable and potential savings and daily peak outside temperature entered as predictors (Model 1). A mixed-effects model (Model 2) was estimated by including a random intercept for households to account for baseline differences across homes.

Model 1 indicated that the regression model was significant, $R^2 = 0.43$, $F(2, 235) = 88.73$, $p < 0.001$. with the following regression equation:

Temperature Penalty (°F) = -0.60 + 0.724 × Potential Savings (USD) + 0.015 × Daily Peak Outside Temp, $R^2 = 0.43$.

Potential savings significantly predicted temperature penalty, $b = 0.724$, SE = 0.055, $t = 13.27$, $p < 0.001$. This means that when users switched into Comfort mode, each additional one-dollar increase in the cost difference between Comfort and Eco modes was associated with a 0.72°F larger gap between the Comfort and Eco target temperatures. In practical terms, users were willing to "pay" for cooler indoor temperatures: for example, a $3 difference corresponds to a predicted 2.17°F increase in the Comfort-Eco setpoint gap (0.724 × 3). This reflects a direct cost-comfort trade-off, where users assign tangible economic value to cooler indoor environments. Daily peak outside temperature also significantly predicted the penalty, $b = 0.015$, SE = 0.007, $t = 2.06$, $p = 0.040$, indicating that hotter outdoor conditions were associated with slightly larger adjustments when entering Comfort mode. Because the intercept does not represent meaningful values within the observed predictor range, it is not interpreted.

Model 2 produced nearly identical fixed-effect estimates once household-level differences were accounted for. Potential savings remained a strong predictor of temperature penalty, $\beta = 0.745$, SE = 0.058, $z = 12.92$, $p < 0.001$, again demonstrating that users systematically widened the Eco-Comfort temperature gap as the monetary value of the cooling increased. Daily peak outside temperature showed a marginal effect, $\beta = 0.014$, SE = 0.007, $z = 1.87$, $p = 0.062$, consistent with Model 1 in suggesting a small positive association with the penalty. The variance of the random household intercept was estimated at 0.036, indicating modest but meaningful differences across homes in their baseline cooling preference tendencies.

3.2. Cost-saving nudges for clothes washers, dryers, and dishwashers

3.2.1. Distribution of appliance activations across peak-hour scenarios

Scenario 1 (spontaneous avoidance) and scenarios 3–4 (deliberate delay via the delay button) were aggregated into a single "peak hours avoidance" category, which accounted for 1,421 of 1,733 activations (82.0%), whereas 312 activations (18.0%) remained in the "peak hours usage" category. At the home appliance level, avoidance rates varied substantially, ranging from 65.3% for the Home 8 dishwasher to 98.8% for the Home 2 dishwasher. Appliance–level descriptive means suggested higher avoidance for dishwashers (M = 85.1%), followed by washers (M = 81.1%) and dryers (M = 79.2%). However, these differences were not statistically significant ($F = 0.852$, $p = 0.447$), indicating that peak-hour avoidance behavior was broadly consistent across appliance types. Peak-hour avoidance and usage rates by appliance and household are summarized in Table 3.

3.2.2. Change in the percentage of daily appliance load during peak hours compared to baseline

To evaluate temporal shifts in appliance usage, the daily power load of each appliance (in watts) was decomposed into hourly proportions. Specifically, the variable representing hourly usage share was defined as the percentage of each appliance's total daily power load consumed during each hour (i.e., hourly load / total daily load × 100). Using percentage-based metrics helped normalize for seasonal variations or fluctuations in total load due to external factors, such as weather or laundry volume, thereby isolating the behavioral change in temporal usage patterns. An independent-samples t-test was used to compare the daily peak-time share (pct_peak), defined as the percentage of each appliance's total daily power load between 17:00 PM and 19:59 PM, before (PreFeature) and after (WithFeature) the feature implementation. The comparison was conducted separately for each appliance (washer, dryer, dishwasher). For example, daily peak-hour shares from the pre-feature period were statistically compared with those from the post-

Table 3
Peak-hour avoidance and usage rates by appliance and household.

Home	Appliance	Peak hours avoidance (n/%)	Peak hours usage (n/%)
2	dishwasher	79 (98.8%)	1 (1.2%)
3	washer	59 (81.9%)	13 (18.1%)
	dryer	64 (84.2%)	12 (15.8%)
	dishwasher	36 (81.8%)	8 (18.2%)
4	washer	139 (88.0%)	19 (12.0%)
	dryer	123 (75.9%)	39 (24.1%)
	dishwasher	52 (88.1%)	7 (11.9%)
5	washer	34 (79.1%)	9 (20.9%)
	dryer	35 (81.4%)	8 (18.6%)
	dishwasher	62 (84.9%)	11 (15.1%)
6	washer	178 (84.4%)	33 (15.6%)
	dryer	199 (83.3%)	40 (16.7%)
	dishwasher	88 (91.7%)	8 (8.3%)
7	dryer	37 (77.1%)	11 (22.9%)
8	washer	104 (72.2%)	40 (27.8%)
	dryer	100 (73.5%)	36 (26.5%)
	dishwasher	32 (65.3%)	17 (34.7%)
All	**All**	**1421 (82.0%)**	**312 (18.0%)**

feature period across all homes and days for the washer. The resulting t-statistics and p-value were displayed on each corresponding plot to indicate whether the change in peak-hour usage was statistically significant. Across the full PreFeature vs. WithFeature period, the washer exhibited a significant reduction in daily peak-hour share from M = 19.59% to M = 14.60% (−4.99%), $t(1158) = 3.01$, $p = 0.003$, d = -0.20, whereas changes for the dryer, $t(967)$ = -0.59, $p = 0.558$, $d = 0.05$, and dishwasher, $t(1352)$ = -0.04, $p = 0.968$, $d = 0.00$, were nonsignificant. Only the washer thus consistently shifted usage away from peak hours following the intervention, as shown in Fig. 9.

Additionally, to allow a consistent comparison and to capture the period when the effect was most pronounced, the baseline and intervention periods were aligned into equivalent durations. Two retrospective comparison windows were examined. First, one-month windows compared the first month of the baseline (September 2-October 1) to the final month of the intervention (February 13-March 13). During this window, the dishwasher's peak–hour load fell significantly from M = 17.16% to M = 9.67% (−7.49%), $t(414) = 2.19$, $p = 0.029$, d = -0.27; the washer showed a marginal decrease from M = 20.33% to M = 14.91%, $t(354) = 1.95$, $p = 0.052$, d = -0.21; and the dryer did not change significantly, $t(297)$ = -0.72, $p = 0.475$, $d = 0.09$. These results indicate that the intervention's effect on reducing peak-period usage became more evident in the latter stages, particularly for the dishwasher. Second, two-month windows compared the full baseline period (September 2-November 7) to the final two months of the intervention (January 8-March 13). In this comparison, only the washer exhibited a significant reduction in peak–hour share, decreasing from M = 19.59% to M = 14.76% (−4.83%), $t(792) = 2.58$, $p = 0.010$, d = -0.19. Changes for the dishwasher, $t(925) = 0.73$, $p = 0.463$, d = -0.06, and dryer, $t(662)$ = -1.28, $p = 0.202$, $d = 0.11$, were nonsignificant.

3.2.3. Impact of peak-hour avoidance on appliance-level power reduction

To examine whether reductions in power load differed depending on how actively households avoided peak hours, homes were divided into two groups based on the frequency of off-peak appliance use. Households that more frequently operated appliances during off-peak hours, either spontaneously (scenario 1) or by using the delay feature (scenarios 3 and 4), were categorized as high-avoidance users. The grouping was based on the median proportion of off-peak usage, calculated as the share of all appliance activations that occurred in off-peak periods. Median values used for classification were 0.82 for the washer, 0.81 for the dryer, and 0.87 for the dishwasher, indicating that over 80% of appliance use occurred outside peak hours in high-avoidance households. The mean power reduction (in watts) was calculated as the difference between the average consumption before November 8 and the average consumption thereafter. For the washer, homes with low avoidance (n = 3) reduced power by M = -1.62 W (SD = 1.53), whereas high-avoid homes (n = 2) reduced power by M = -2.13 W (SD = 0.25); this difference was not statistically significant, $t(3)$ = -0.45, $p = 0.686$, d = -0.41. For the dryer, low-avoid homes (n = 3) achieved a reduction of M = -3.88 W (SD = 2.42) compared to high-avoid homes (n = 2), which reduced M = -21.84 W (SD = 9.75); this difference was significant, $t(3)$ = -3.30, $p = 0.046$, d = -3.01. For the dishwasher, low-avoid homes (n = 3) reduced consumption by M = -1.77 W (SD = 3.98) and high-avoid homes (n = 3) by M = -5.23 W (SD = 0.94), a non-significant difference, $t(4)$ = -1.46, $p = 0.217$, d = -1.20, as presented in Fig. 10. These findings indicate that greater peak-avoidance behavior was associated with substantially larger power reduction for the dryer, but not for the washer or dishwasher, over the full post-launch period. This pattern suggests that running appliances during peak hours forces them to work harder under high grid demand, so delaying use to off-peak times reduces the load and saves energy.

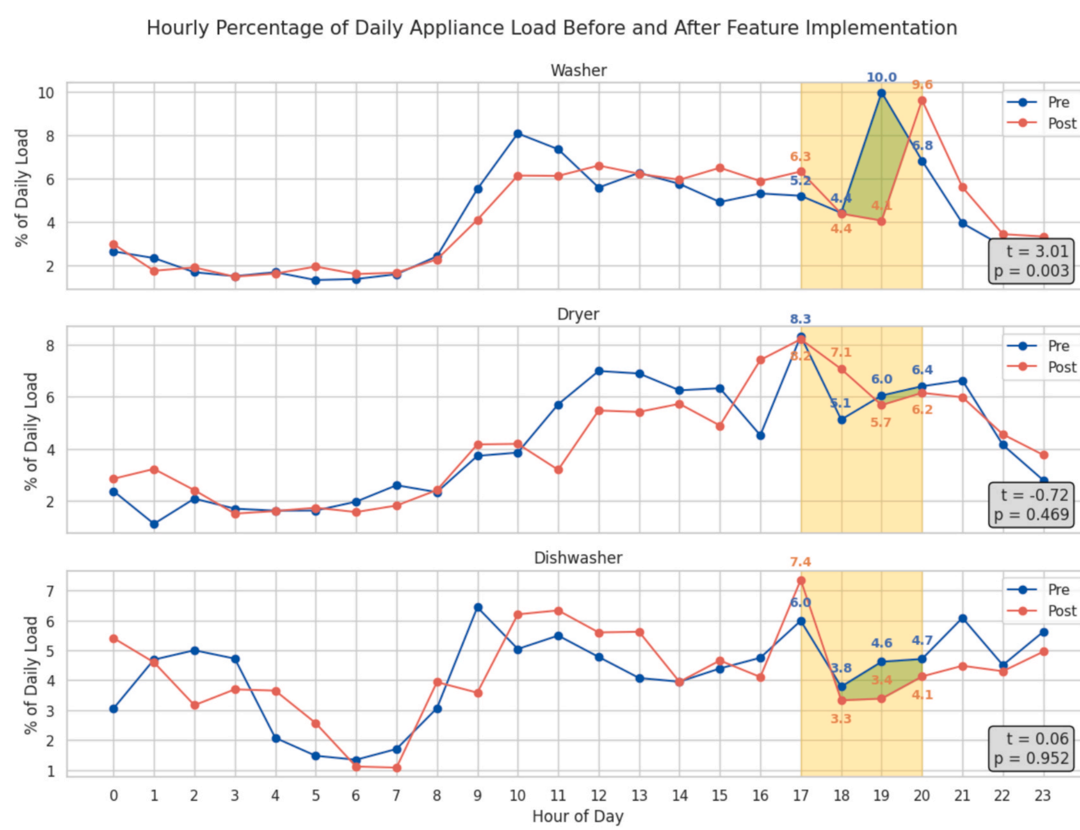

Fig. 9. Percentage of power load (W) before and after feature implementation by appliance and hour of day.

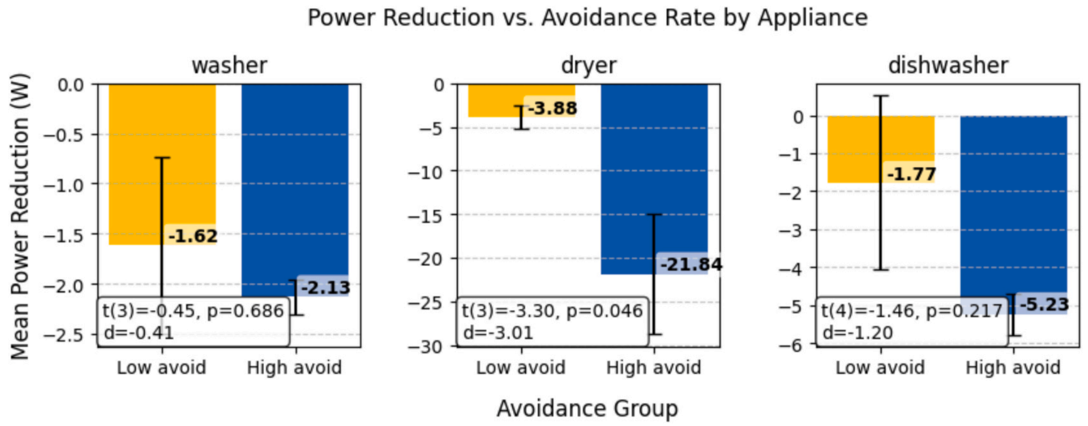

Fig. 10. Power reduction (W) comparison between low- and high-avoidance groups for each appliance.

3.3. Incentive for delaying clothes washers, clothes dryers, and dishwashers

3.3.1. Acceptance rate by time slots

Acceptance rates were highest at night across all three appliances and were lowest in the morning, a pattern that was consistent but varied in magnitude by appliance, as shown in Fig. 11. Chi-square analyses confirmed significant time-of-day effects for washers, $\chi^2(3) = 20.16$, $p < 0.001$; dryers, $\chi^2(3) = 38.32$, $p < 0.001$; and dishwashers, $\chi^2(3) = 88.44$, $p < 0.001$. For washers, nighttime acceptance (M = 67.8%, SD = 46.9) exceeded morning (M = 44.4%, SD = 49.9; $p = 0.003$, $h = 0.48$) and peak hours (M = 44.7%, SD = 50.0; $p = 0.003$, $h = 0.47$), but showed no significant difference from the afternoon (M = 56.4%, SD = 49.7). For dryers, nighttime acceptance (M = 63.2%, SD = 48.4) was higher than morning (M = 33.6%, SD = 47.4), afternoon (M = 42.4%, SD = 49.6), and peak hours (M = 36.0%, SD = 48.2), $ps \leq 0.001$, with medium effect sizes (h = 0.42–0.60). No significant differences were found among morning, afternoon, and peak hours themselves. For dishwashers, nighttime acceptance (M = 83.3%, SD = 37.4) was significantly higher than in the morning (M = 35.8%, SD = 48.2), afternoon (M = 57.6%, SD = 49.8), and peak hours (M = 40.0%, SD = 50.3), all $ps < 0.01$, with large effect sizes (h = 0.58–1.02). In contrast, morning and afternoon acceptance did not significantly differ from each other, and neither did morning and peak hours, indicating that the major contrast for dishwashers lies between nighttime and all other slots. Taken together, these findings demonstrate that nighttime consistently yielded the highest acceptance rates across all appliances, with the strongest contrasts emerging between night and all other time slots, while non-nighttime periods rarely differed from each other in a meaningful way.

3.3.2. Acceptance rate by incentive amount

Acceptance rates generally increased with higher offer amounts across all appliances. For the dishwasher, acceptance rose from 49.5% (n = 95) at $0 to 54.0% (n = 87) at $0.50 and reached 82.4% (n = 85) at $1.00, remaining high at 73.7% (n = 99) for $2.00 and 82.2% (n = 107) for $4.00. The dryer showed a similar trend, with acceptance increasing from 26.3% (n = 99) at $0 to 36.1% (n = 119) at $1.00, 36.3% (n = 124) at $2.00, 49.2% (n = 122) at $4.00, and 70.4% (n = 159) at $8.00. For the washer, acceptance grew from 13.0% (n = 77) at $0 to 50.0% (n = 2) at $0.50, 46.0% (n = 87) at $1.00, 50.4% (n = 113) at $2.00, 65.0% (n = 140) at $4.00, and 76.2% (n = 130) at $8.00. These patterns indicate a clear positive association between incentive amount and likelihood of acceptance. For all three appliances, the probability of acceptance increased with higher monetary offers. The dishwasher showed a sharp increase at $1.00, followed by relatively stable high acceptance. In contrast, the dryer and washer demonstrated more gradual but consistent upward trends, particularly notable at $4.00 and $8.00. These visual patterns support the regression findings that incentives have a positive influence on acceptance behavior, as shown in Fig. 12.

Logistic regression revealed that increasing the offer amount significantly raised the likelihood of acceptance for each appliance ($p < 0.001$). The estimated increase in log-odds per one-dollar increase in offer was $\beta = 0.277$ for the washer ($R^2 = 0.094$, AIC = 690.0, BIC = 698.6), $\beta = 0.226$ for the dryer ($R^2 = 0.075$, AIC = 799.2, BIC = 808.1), and $\beta = 0.378$ for the dishwasher ($R^2 = 0.045$, AIC = 565.5, BIC = 573.9). Because logistic regression coefficients reflect changes in log-odds, they were exponentiated to obtain odds ratios (OR = e^{β}). For

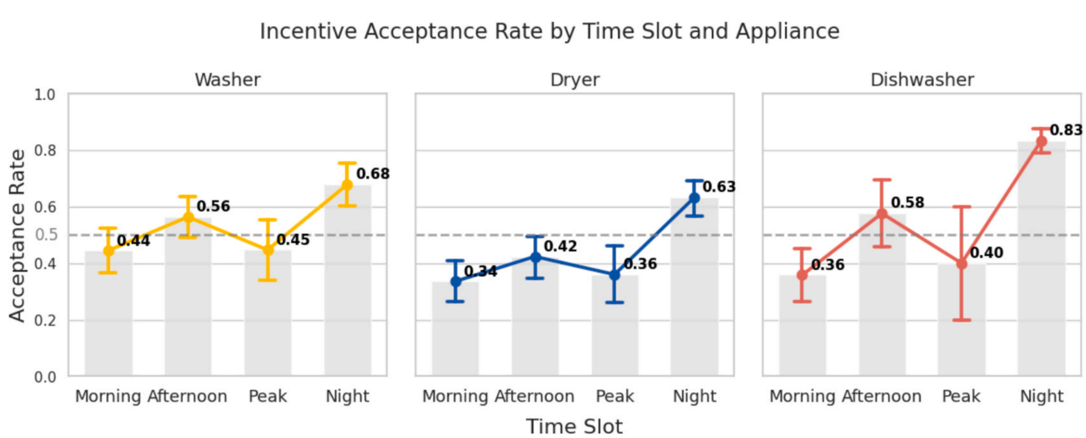

Fig. 11. Acceptance rates by time slot: morning (4 AM-12 PM), afternoon (12 PM-5 PM), peak (5 PM-8 PM), night (8 PM-3 AM) by appliance. Acceptance rates reflect the share of offers that users accepted.

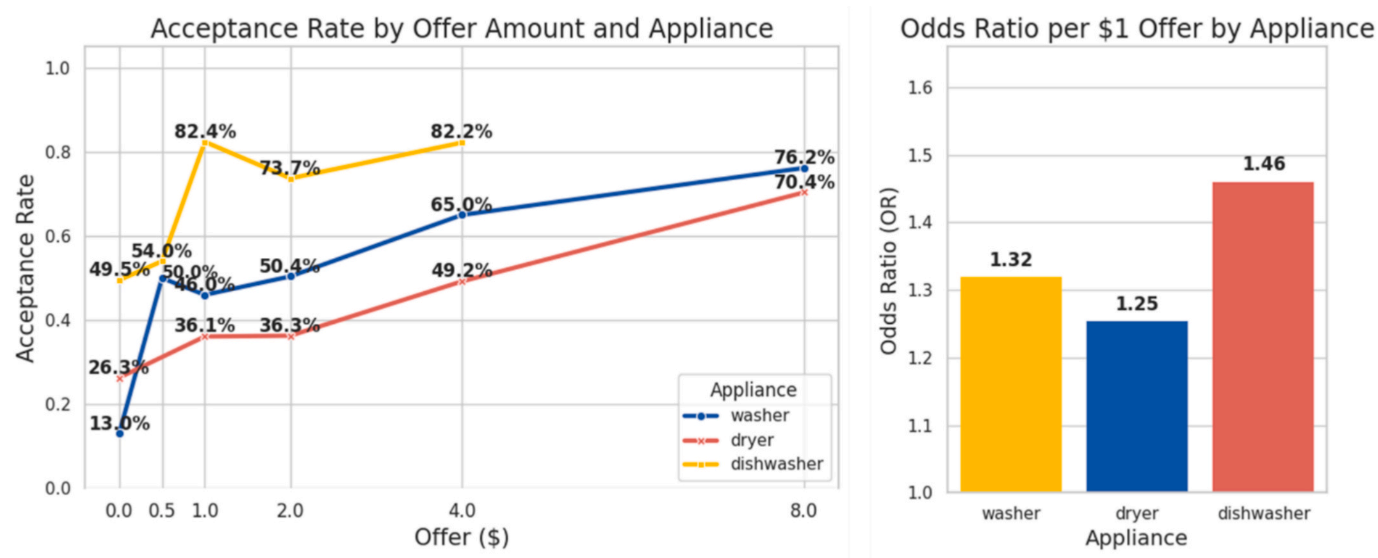

Fig. 12. Acceptance rates by offer amount (left) and odds ratios per $1 offer (right) by appliance.

instance, the coefficient for the washer ($\beta = 0.277$) yielded an OR of 1.319 (95% CI [1.230, 1.414]), indicating a 32% increase in odds per dollar. The resulting ORs per $1 increase were 1.319 for the washer, 1.254 (95% CI [1.183, 1.328]) for the dryer, and 1.460 (95% CI [1.251, 1.703]) for the dishwasher, corresponding to 32%, 25%, and 46% increases in odds, respectively, as presented in right panel of Fig. 12. An interaction model including offer $\times$ appliance terms revealed no significant interactions, suggesting that the marginal effect of the offer amount on acceptance did not vary significantly across appliance types.

4. Discussion

The study reveals a precise numerical relationship between temperature settings and cost penalties, uniquely quantifying users' willingness to trade additional expense for incremental cooling in a residential setting. Although baseline preferences varied somewhat across households, these differences were modest, indicating that the observed trade-off pattern was broadly consistent. Even during extreme outdoor heat, the willingness to sacrifice comfort for savings rose only slightly, indicating that immediate economic cues exert a stronger influence on decision–making than weather conditions alone. These results suggest that transparent, mode-specific cost information can effectively nudge user decisions without forcing a binary "comfort versus savings" choice. Rather than uniformly pushing users toward energy-saving settings, explicit pricing for each mode enables self-regulation, letting users decide when extra comfort justifies the expense and when a modest temperature compromise yields savings. This has implications for thermostat interface design and broader energy management strategies, as it highlights how framing and cost visibility can shift user behavior in measurable, predictable ways. Nevertheless, users still chose the higher–cost Comfort mode more often than Eco mode, willingly paying an extra $0.97 per mode-selection event and using more energy to achieve only 1.54°F of additional cooling. Regression analysis confirmed that users placed greater importance on lowering the temperature, willingly accepting extra costs of about one dollar for every 0.72°F of additional cooling through Comfort mode. This aligns with previous studies showing that users are willing to pay more to maintain a comfortable indoor temperature, emphasizing that temperature satisfaction often outweighs pure cost considerations [44–46]. For example, Berto et al. [44] confirmed a significant willingness to pay for all comfort aspects, with the highest share allocated to thermal comfort (51%, €377.94/m^2). This was followed by visual comfort (22%, €166.83/m^2), acoustic comfort (16%, €119.60/m^2), and indoor air quality (11%, €79.21/m^2). These patterns demonstrate that binary (eco and comfort) notifications may be insufficient, since users remain willing to pay more to achieve cooler indoor temperatures. Instead, notifications should display cumulative costs alongside temperature impacts, offer finer–grained tiers such as Comfort Plus, Comfort and Eco Plus with small incremental price differences, send timely alerts [32,47] when users reach their cost–per–degree limits, or provide energy–saving tips [31] to guide them toward more energy–efficient choices without sacrificing their preference for cooler indoor temperatures. Furthermore, by deploying smart thermostats that adapt to residents' daily routines, it is possible to generate and simulate occupancy schedules from large-scale thermostat data, thereby realizing more precise energy savings [13,48].

Delaying appliance use via cost-saving nudges proved highly effective. Aggregating spontaneous avoidance and intentional delay scenarios, 82.0% of appliance cycles occurred during off-peak hours while savings information was displayed. Differences between appliances were not statistically significant, indicating the nudge interface communicated savings opportunities in an appliance-independent manner. Temporal analyses showed the washer exhibited the most robust response, with a significant reduction in daily peak–hour load share across the full pre– versus post–feature period. However, in matched one-month windows capturing the intervention's maturity, the dishwasher's peak–hour share fell notably, suggesting adoption for certain appliances may strengthen over time. Finally, power-reduction comparisons between high-avoidance and low-avoidance households revealed that greater off-peak usage resulted in larger energy savings for the dryer, highlighting the value of targeting high-demand devices for behavioral interventions. Providing real-time, direct feedback on potential savings from delaying appliances effectively guides behavior, encouraging users to shift their usage away from peak hours and reduce overall energy loads. This reflects previous findings that immediate feedback is powerful in influencing everyday energy habits, while longer-term strategies, such as detailed bills and annual reports, foster broader behavioral changes and informed investment decisions. Prior research indicates that direct feedback can achieve savings of around 5–15%, whereas indirect feedback yields about 0–10% [49].

When incentives were applied, even a $0.50 offer achieved over 50% acceptance for both washers and dishwashers, and acceptance rates continued to rise with larger payouts. These patterns are consistent with prior findings on incentive-based demand response for residential appliances [50]. In contrast, dryers only approached a 50% acceptance rate at the $4.00 incentive level. This suggests that homeowners are more willing to delay washer and dishwasher cycles than dryer cycles. Looking at acceptance by time of day, regardless of incentive amount, night-time delays (after 8 PM) were most common. The dishwasher in particular recorded an 83.3% acceptance rate at night, indicating that users readily postponed dishwasher use during typical off-peak hours, even without the highest incentive levels, likely reflecting household routines. Additionally, regression analysis confirmed that dishwashers were the most responsive to increasing rewards: each additional dollar raised the odds of acceptance by 46%, compared to 32% for washers and 25% for dryers, with dryers remaining the least responsive of the three.

A core principle of a smart home notification system is to determine how aggressively to drive behavior change and to tailor intervention intensity for each appliance. These insights suggest that intervention strength should be dynamically adjusted to maximize engagement without causing fatigue, reflecting each device's unique characteristics. The delay feature prompted all three appliances to shift their cycles off-peak, but the impact on peak-hour loads varied by device. Both washers and dishwashers showed significant reductions in their percentage of daily power load during peak periods when comparing data from before and after the intervention. Dryers, although similarly delayed, did not exhibit a significant group-level drop in peak-hour usage. Instead, measurable energy savings for dryers only appeared when comparing households with high versus low delay rates. Homes that frequently used the delay function achieved significantly greater power reductions. This suggests that while dryers respond to scheduling prompts, their higher per-cycle energy [51] draw means reliable savings emerge only under consistent, repeated delay use. By calibrating nudge strength and reward levels to each appliance's demand profile, and adjusting them based on real-time user response, smart-home systems can achieve sustained load shifting. Utilities and platform designers should therefore adopt an appliance-specific range of behavioral prompts, from gentle awareness cues to robust financial incentives, to ensure optimal engagement and energy savings across all household devices.

The extended field deployment of smart-home features, especially cost-related notifications across multiple appliances in real-world settings, provides valuable insights into behavioral changes and energy consumption. Observations of actual load-shifting behavior over several months highlight the practical impact of these interventions. However, several factors limit the generalizability of these findings. This field study required provisioning smart appliances, which limited the number of participating households. Replicating this work with a larger and more diverse sample of homes would strengthen confidence in the results. Although the dataset spans nearly one year and captures a wide range of daily behaviors, subgroup analyses sometimes rely on small sample counts, particularly when comparing households by avoidance levels or appliance type. In addition, all participants experienced the system features in the same fixed order. While this ensured consistency across households, the ordering may have introduced learning or anchoring effects that influenced participants' interactions with later features. Similarly, repeated exposure to varying incentive amounts may have shaped participants' expectations over time, potentially influencing subsequent acceptance decisions. Future studies should mitigate potential order effects by counterbalancing or randomizing feature exposure. Furthermore, although the baseline and intervention periods were aligned to equivalent durations for the delay nudge analysis, before-and-after comparisons can still be influenced by time-related trends, making it difficult to attribute all differences solely to the intervention. Lastly, the study collected limited demographic and lifestyle information from residents [52], which prevents analysis of how income levels [53], daily routines [48], and household composition [54] influence intervention effectiveness. This limitation may also affect the interpretation of willingness-to-pay results, as households with greater financial flexibility may respond differently to cost-related notifications. Future research should gather detailed data on occupancy schedules and socio-economic factors to enable targeted nudge designs. Extended studies that include a control group would allow a more rigorous assessment of intervention persistence. Developing adaptive or personalized nudge strategies that adjust message timing, format, and incentive levels based on household profiles also remains an important avenue for research. Addressing these gaps will support the creation of scalable and appliance-specific strategies for sustained energy savings in smart-home environments.

5. Conclusion

This study explored the effects of cost-related notifications, including nudges, delivered through smart appliances, on user behavior and power load shifting. The practical impact of these features highlights their potential for integration into smart-home platforms and utility demand-response programs. Cost-related information was effectively applied across all interventions, demonstrating meaningful influence on user decisions and energy use. Field deployment across multiple homes revealed that users were willing to pay more for air conditioning to achieve lower indoor temperatures. At the device level, washers and dishwashers achieved substantial peak-period load reductions with simple delay prompts, whereas dryers, despite being delayed, only translated that rescheduling into measurable power savings in high-usage households, underscoring the need for more consistent and stronger incentive-based interventions for high-demand appliances. These findings show that both delay and incentive nudges produced distinct responses across appliances. The study emphasizes that applying nudges with the right intensity and design for each appliance and each behavioral intention can drive tailored behavior change and measurable energy savings. This approach demonstrates the potential for strategically reducing residential energy demand during peak periods by leveraging targeted interventions and cost-related feedback, ultimately contributing to improved grid stability, optimized resource allocation, and greater overall energy efficiency within the smart home environment.

CRediT authorship contribution statement

Seonghyuk Son: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation. **Keith Graeber:** Supervision, Resources, Project administration, Methodology. **Hideki Shimada:** Methodology, Formal analysis. **Jae Yong Suk:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition.

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Jae Yong Suk reports financial support was provided by New Energy and Industrial Technology Development Organization (NEDO). Jae Yong Suk reports financial support was provided by Panasonic Holdings Corp. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Table A
Home characteristics and appliances for the eight selected homes.

Home Attribute	Home 1	Home 2	Home 3	Home 4	Home 5	Home 6	Home 7	Home 8
Home Vintage	2001	1993	1996	2007	2018	2003	2006	1993
Home Configuration	Two story	Single story	Single story	Two story	Two story	Two story	Two story	Single story
Frame Material	Wood	Wood	Wood	Wood	Wood	Wood	Wood	Wood
Roof Type	Composition	Composition	Shake shingle	Shake shingle	Tile	Shake shingle	Shake shingle	Composition
Exterior Material	Wood	Wood	Brick, wood	Stucco, wood	Stucco, wood	Stone, stucco, wood	Stucco, wood	Stucco, brick, wood
Living Space	2,192 sqft	1,198 sqft	2,011 sqft	1,187 sqft	1,679 sqft	2,231 sqft	1,722 sqft	1,385 sqft
Residents	4	1	2	5	2	5	1	3
Pet(s)	Yes	No	Yes	Yes	Yes	Yes	Yes	No
Bedrooms	4	3	3	3	3	4	3	3
Full Bathrooms	3	2	2	2	2	3	2	2
Electric Appliances	Water heater, clothes washer	Water heater, clothes washer,	Clothes washer, clothes dryer, cooktop	Clothes washer, clothes dryer	Clothes washer, clothes dryer	Clothes washer, clothes dryer	Clothes washer, clothes dryer	Water heater, clothes washer, clothes dryer
Gas Appliances	Clothes dryer, range	Clothes dryer, range	Water heater, oven	Water heater, range	Tankless water heater, range	Water heater, range	Water heater, range	range
Smart Appliances	Rheem heat pump hot water heater, 4 Philips Hue light bulbs	Rheem heat pump hot water heater	Two Honeywell thermostats LG clothes washer, LG clothes dryer	LG clothes washer, LG clothes dryer	Nest thermostat, three Lutron dimmer switches, garage door opener	Ecobee thermostat, range, 1 Lutron dimmer switches	Nest thermostat, 3 Feit LED light bulbs	Nest thermostat, Rheem heat pump hot water heater, GE clothes washer, GE clothes dryer
Other Appliances / Systems / Notes	None	Solar, EV charger, and extra roof insulation	None	None	Solar	None	None	None

Table B
Summary of total and on-peak (5–8 PM) home energy consumption during July for each load group, displayed as the percentage of energy used in the home (%) and total Watt-hours of energy used (Wh).

Load Group	Energy Type	Home 1	Home 2	Home 3	Home 4	Home 5	Home 6	Home 7	Home 8
AC	Total (%, kWh)	35.0%, 245	29.0%, 172	52.6%, 390	38.1%, 392	47.1%, 281	34.0%, 586	47.6%, 358	45.8%, 491
	On-Peak (%, Wh)	39.2%,51612	16.6%,7873	38.3%,127234	51.3%,100369	55.1%,57290	41.0%,116169	50.6%,67686	62.3%,158145
Water heater	Total (%, kWh)	4.8%, 33	1.6%, 9	N/A	N/A	1.0%, 6	N/A	N/A	3.4%, 37
	On-Peak (%, Wh)	2.4%, 3102	0.5%, 230	N/A	N/A	0.7%, 751	N/A	N/A	4.0%, 10,249
Clothes Washer	Total (%, kWh)	0.5%, 3	1.5%, 9	1.3%, 10	1.3%, 14	0.7%, 4	0.3%, 5	0.0%, 0	0.8%, 8
	On-Peak (%, Wh)	0.5%, 539	2.1%, 991	0.5%, 1790	0.4%, 688	0.0%, 4	0.3%, 822	0.1%, 89	0.8%, 2091
Ventilation	Total (%, kWh)	0.0%, 4	0.5%, 3	0.1%, 1	N/A	14.5%, 86	7.1%, 122	1.2%, 84	2.0%, 22
	On-Peak (%, Wh)	0.2%, 262	1.0%, 429	0.2%, 594	N/A	15.0%, 15,638	8.1%, 22,911	8.57%, 11,460	0.4%, 993
Refrigerator	Total (%, kWh)	8.9%, 62	4.3%, 26	7.8%, 58	8.3%, 85	9.4%, 56	4.4%, 76	15.1%, 114	7.1%, 76
	On-Peak (%, Wh)	7.1%, 9350	9.8%, 4656	2.4%, 8047	5.5%, 10,759	7.8%, 8055	3.7%, 10,495	11.7%, 15,641	4.5%, 11,390
Range	Total (%, kWh)	Gas range	0.8%, 4.8, Electric hot plate; Gas range	2.0%, 14.71	Gas range	Gas range	Gas range	1.3%, 10.03	Gas range
	On-Peak (%, Wh)	Gas range	1.1%, 529	4.5%, 8943	Gas range	Gas range	Gas range	6.2%, 8270	Gas range

(continued on next page)

Table B (*continued*)

Load Group	Energy Type	Home 1	Home 2	Home 3	Home 4	Home 5	Home 6	Home 7	Home 8
Other Plug	Total (%, kWh)	0.3%, 2	25.7%, 152	0.0%, 0	0.1%, 1	3.4%, 20	1.9%, 32	3.5%, 26	4.0%, 43
	On-Peak (%, Wh)	0.2%, 286	29.5%, 14,266	2.6%, 0	0.1%, 141	2.9%, 2164	1.8%, 4956	2.8%, 3786	2.2%, 5501
Other Circuit	Total (%, kWh)	N/A	N/A	N/A	N/A	0.018%, 0.1	N/A	N/A	N/A
	On-Peak (%, Wh)	N/A	N/A	N/A	N/A	0.0%, 13	N/A	N/A	N/A
Microwave	Total (%, kWh)	0.9%, 6	0.8%,5	N/A	N/A	N/A	1.3%, 22	0.6%, 5	0.4%, 5
	On-Peak (%, Wh)	1.3%, 1740	1.9%, 879	N/A	N/A	N/A	1.5%, 4241	2.6%, 3510	0.3%, 728
Lights / some plugs	Total (%, kWh)	18%, 126	12.4%, 74	22.6%, 168	36.2%, 373	18.9%, 113	18.3%, 315	4.1%, 31	21.9%, 235
	On-Peak (%, Wh)	12.6%, 16,624	14.8%, 7038	19.9%, 39,604	30.5%, 59,730	15.6%, 16,209	14.1%, 39,945	3.1%, 4138	12.9%, 32,711
EV	Total (%, kWh)	N/A	17.7%, 105	N/A	N/A	N/A	N/A	N/A	N/A
	On-Peak (%, Wh)	N/A	9.7%, 4614	N/A	N/A	N/A	N/A	N/A	N/A
Solar	Total (%, kWh)	N/A	−52.2%, −310	N/A	N/A	−86.9%, −518	N/A	N/A	N/A
	On-Peak (%, Wh)	N/A	−59.0%, 28,016	N/A	N/A	−55.8%, −58002	N/A	N/A	N/A
Entertainment	Total (%, kWh)	29.1%, 203	2.9%, 17	8.7%, 65	8%, 83	0.9%, 5	23.0%, 397	13.8%, 104	5.2%, 56
	On-Peak (%, Wh)	26.1%, 34,353	11.7%, 5531	4.5%, 8851	7.2%, 14,132	1.1%, 1124.6	22.2%, 62,916	9.2%, 12,382	3.1%, 7805
Clothes Dryer	Total (%, kWh)	Gas	Gas dryer	3.5%, 26	N/A	2.2%, 13	7.9%, 136	1.8%, 14	5.2%, 56
	On-Peak (%, Wh)	Gas	Gas dryer	0.9%, 1705	N/A	0%, 0	6.5%, 18,545	1.5%, 1947	6.9%, 17,511
Dishwasher	Total (%, kWh)	0.0%, 0	2.1%, 12	1.3%, 10	0.4%, 4	1.1%, 7	1.1%, 18	0.6%, 5	0.9%,10
	On-Peak (%, Wh)	0.0%, 0	0.0%, 0	0.9%, 1696	0.0%, 5.	1.4%, 1472	0.0%, 0	0.0%, 6	0.9%, 2177

Data availability

Data will be made available on request.

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