Planning to Save Energy: How Information Format Affects Accuracy

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Abstract

This study aims to examine how the format of energy information impacts individuals' ability to develop precise energy reduction plans. By manipulating the reference class (kWh, %, USD) and assessing planning accuracy, we seek to determine which format facilitates better comprehension and decision-making.Across two experiments, the kWh format generally led to better accuracy, while the USD format consistently led to the worst performance. These findings highlight the importance of effective information presentation to promote energy conservation, and may contribute to the development of more effective energy communication strategies that can enhance conservation efforts.

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Introduction

- highlight the significant contribution of residential energy consumption to carbon emissions and the potential for substantial reductions. Make point about urgency of climate change? (IPCC (2014) and EIA (2012)).

- Electricity bills are a primary source of energy-use information for consumers and offer a promising avenue for enhancing communication about energy consumption (Fischer, 2008)

Literature Review

Energy poverty continues to be a pervasive issue in the United States Memmott et al. (2021). This challenge partly arises from difficulties in converting information across numerical formats, impeding the development of precise energy reduction plans Reimer et al. (2015). Prior research by Canfield et al. (2017) demonstrated that presenting energy information in tabular formats enhances comprehension relative to graphs.

The way numerical information is presented can significantly affect how individuals process and use that information (Reimer et al., 2015) . The reference class problem highlights that numbers without clear reference points can lead to misinterpretation, as the meaning of a statistic depends on the category or class it refers to (Gigerenzer & Edwards, 2003; Reimer et al., 2015). Presenting energy information in absolute units (e.g., kWh) provides a clear reference class, potentially enhancing comprehension.

The concept of cognitive fit posits that performance improves when the information presentation format aligns with the task requirements (Vessey, 1991), and that such an alignment can reduce cognitive load and enhance accuracy in planning (Shah & Freedman, 2011). For instance, tables are generally more effective than graphs for conveying specific electricity usage data because they facilitate straightforward point reading (Canfield et al., 2017). However, the effectiveness of the format varies with the type of information and individual differences, such as energy literacy, which significantly impacts comprehension and conservation intent. Moreover, the unit in which numerical information is presented influences how decision-makers evaluate and choose between options, with default units increasing value sensitivity (Herberz et al., 2020). In the context of energy, presenting information in terms of multiple translations can increase preference for options aligned with activated objectives, such as pro-environmental values (Ungemach et al., 2018). Furthermore, mental accounting mechanisms, where individuals create mental budgets linking specific consumption acts to specific payments, significantly impact energy decisions and behaviors (Hahnel et al., 2020).

Evidence from research on energy consumption feedback, normative comparisons, and eco-feedback platforms suggests that comprehensible and contextually meaningful data presentations can improve users' ability to plan reductions, especially when these formats are integrated into daily routines (Canfield et al., 2017; Fischer, 2008; Kim et al., 2022; Schwartz et al., 2015). Furthermore, temporal and monetary frames have been shown to alter decision quality, with monthly costs or absolute consumption levels often encouraging more energy-efficient intentions than abstract annual or percentage-based metrics (Gill et al., 2022; Larrick & Soll, 2008). In this context, tailoring reference classes to align with intuitive cognitive processes can help bridge the gap between aggregate reduction goals and targeted, appliance-specific conservation strategies.

Furthermore, research suggests that natural frequencies and absolute numbers are generally easier for individuals to understand compared to percentages or probabilities Hoffrage et al. (2000). In the context of energy conservation, using absolute units may facilitate more accurate planning and decision-making by aligning with intuitive cognitive processing.

Despite existing studies on energy-use communication and format effects, limited research has explored how different numerical representations influence consumers' ability to create accurate energy conservation plans. Specifically, there is a gap in understanding how presenting energy information in absolute units versus percentages or monetary terms affects the precision of planning appliance-specific reductions. Addressing this gap is crucial for developing effective interventions that promote energy conservation behaviors.

Hypotheses

Building on these findings and informed by prior work showing that frequencies (like absolute units in kWh) are easier to comprehend and facilitate more precise decision-making compared to percentages, our study also utilizes a tabular format, but manipulates whether participants must consider energy information presented as absolute units (kWh), percentages (%), or monetary costs (USD). We hypothesize that presenting information in absolute units (kWh) will lead to more accurate household energy conservation planning.

Experiment 1

See Figure 1 for an example of a planning trial as it was seen by participants.

Methods

Participants

We implemented our task and surveys on Qualtrics, and recruited participants through Amazon Mechanical Turk. In Experiment 1, 252 participants were initially recruited, but data from 17 participants were corrupted due to experimenter error, leaving a final sample of 235 participants. Most participants (76%) reported using a calculator to complete the task.

Materials and Design

The study employed a mixed design with reference class (kWh, percentage, USD) as a between-subjects factor and state/family scenario as a within-subjects factor. Each participant completed energy reduction planning tasks for two different states, with state order counterbalanced across participants. The family scenarios featured four households in different climate regions: Texas (Smith family) and California (Adams family) representing warm climates, and Colorado (Wells family) and Massachusetts (Davis family) representing cold climates. We obtain average utility use from each state by CITE SOURCE FOR STATE AVGS?

Procedure

Participants received energy usage data for two hypothetical families and were tasked with creating action plans to meet specified reduction goals by allocating usage across five appliance categories: heating, cooling, water heating, refrigerator, and and other appliances (e.g., TV, lighting).

For each family scenario, the participants were shown a table containing the families utility usage from the prior year, alongside the state averages for each appliance category (both prior year usage and stage averages are always shown in kWh). For each scenario, participants were asked to create two possible action plans to achieve the target reduction in total household energy usage (see Figure 1). Depending on their reference class condition, the target reduction amount presented either in kilowatt-hours (kWh), as percentages of total household usage, or in U.S. dollars. In all conditions, the target reduction was equivalent to a 15% reduction in total household kWh.

The Wells family wants to reduce its household electricity use by 15% next year. Please complete two possible action plans that will help the Wells family achieve this goal. Please enter how many kWh should be used next year by each appliance and the total kWh each plan would use. **Enter only whole numbers.** Try to provide close estimations. You may use a calculator to complete the task.

Note: The Wells family used 9,233 more kWh than the average household in Colorado last year.

	Electricity Used Last Year by the Wells Family (kWh)	Average Electricity Used Last Year by Households in Colorado (kWh)	Action Plan 1	Action Plan 2
Cooling (Central A/C)	697	498		
Heating the Home	18,052	16,411		
Water Heating	11,667	5,832		
Refrigerator	1,370	1,142		
Other (Television, Lighting, Electronics, Washer/Dryer, etc.)	7,982	6,652		
Total kWh	39,768	30,535		

Figure 1: Example trial in the energy planning task. Participants are shown the prior year electricity use of a household, and are tasked with creating a plan for the next year that will meet the energy reduction goal. Study 1 manipulates the format of the reduction goal to be either a percentage (15% given as goal reduction), kilowatt hours (5965 kWh given), or USD ($656)

Additional data collected included:

- **Energy Literacy Quiz**: An 8-item questionnaire assessing participants' knowledge of energy consumption and conversion (DeWaters & Powers, 2011).
- **Calculator Usage Tracking**: Questions determined whether participants used a calculator, paper/pen, or other methods to complete the tasks.
- **Demographic Survey**: Collected information on gender, age, income, education, employment status, and state of residence.
- **Environmental Attitudes Survey**: Assessed participants' pro-environmental attitudes and perceived importance of energy conservation.

Results

Data Analysis

All preprocessing and analyses were carried out in R (Team, 2020) and the tidyverse package (Wickham et al., 2019). Mixed Bayesian regressions were fit using the brms package (Bürkner, 2017), with participants and family scenario (states) set as random effects.

Table 1: Study 1: Summary of planning accuracy by reference class. The table shows performance as both the % of trials where participants matched the goal, and the mean absolute error from the target reduction goal

Reference Class	Avg. % Change	% meeting goal (exact)	% meeting goal (close match)	Abs. Deviation	Log Abs. Deviation
kWh	0.22	0.38	0.54	0.03	-3.7
Percentage	0.21	0.22	0.40	0.06	-3.1
USD	0.23	0.10	0.22	0.10	-2.4

Table 1 that participants in the kWh condition met the target goal 38% of the time, compared to 22% for the Percentage condition and 10% for the USD condition. Moreover, the kWh reference class exhibited smaller deviations from the target reduction, suggesting that participants performed more accurately when the goal was framed in kWh rather than percentages or USD.

As shown in Table 1, participants in the kWh condition exactly met the target reduction goal 38% of the time, significantly outperforming those in the Percentage (22%) and USD (10%) conditions. Furthermore, the kWh reference class exhibited notably smaller mean absolute deviations (0.03) compared to Percentage (0.06) and USD (0.10), suggesting that presenting the reduction goal in absolute units facilitated more precise allocations.

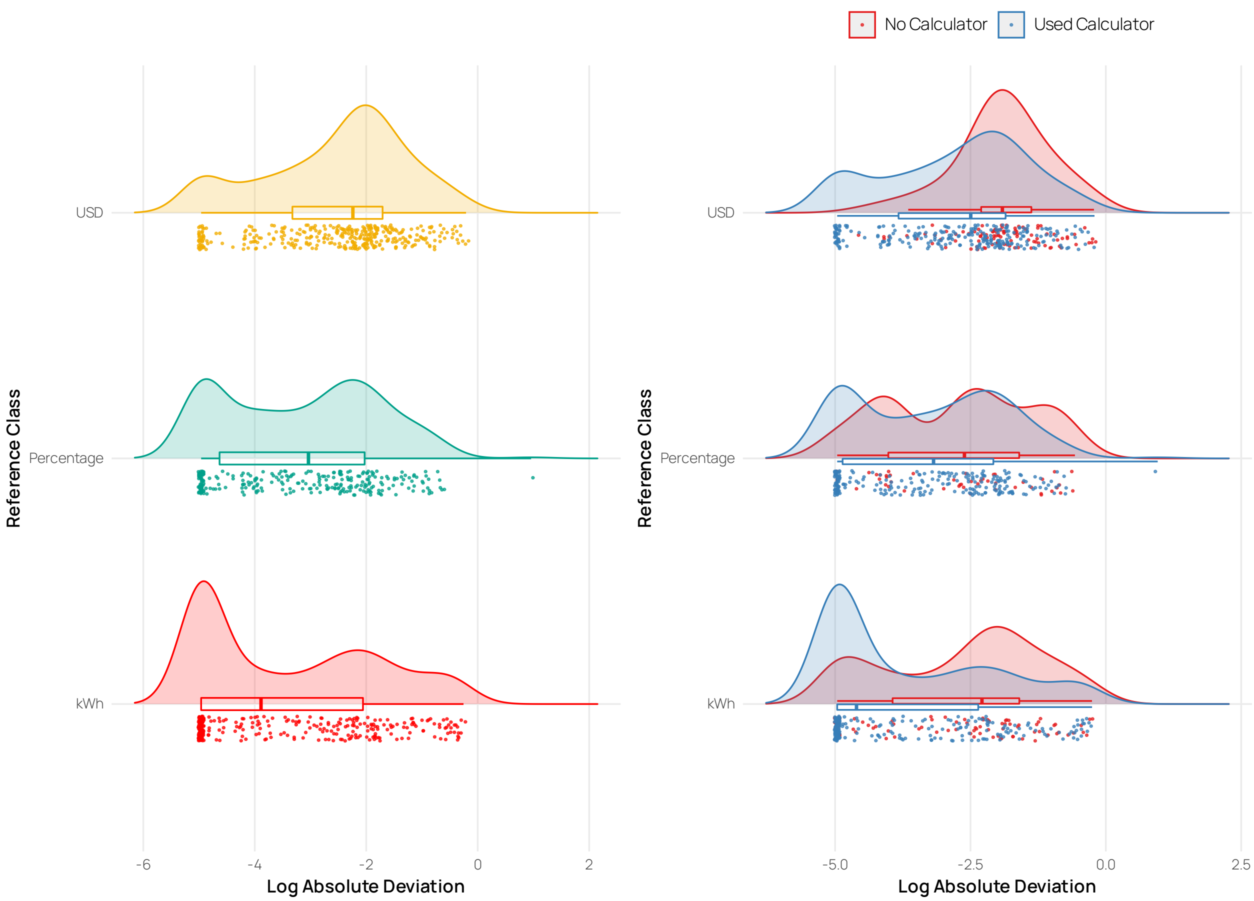

Figure 2: Study 1: Distribution of log absolute error by reference class.

Table 2: Study 1: The table shows the percentage of participants who fell into each accuracy level for each reference class condition (percentages of kWh, $, and USD columns reflect within condition percentages). The combined group column reflects the percentage of participants in each accuracy level when aggregating across across all reference class conditions.

Accuracy Level	kWh	Percentage	USD	Combined Groups %
Exact match	37.5%	22.1%	9.8%	22.6%
0.01-2% error	15.1%	17.6%	11.2%	14.4%
2.01-15% error	27.6%	43.4%	49.2%	40.3%
Over 15% error	19.9%	16.9%	29.8%	22.8%

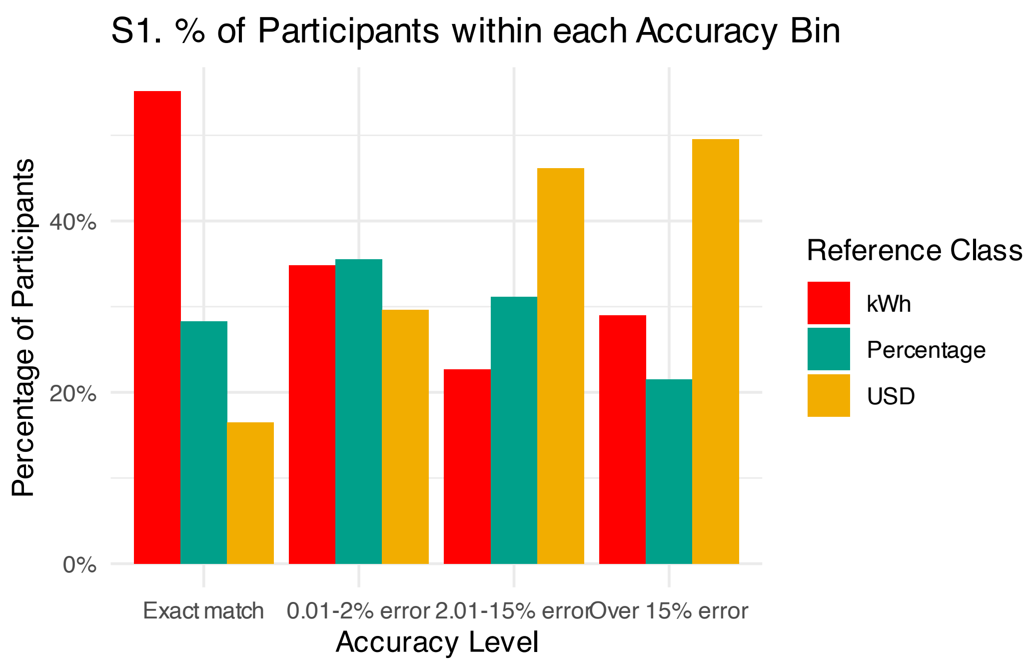

Figure 3: Study 1: Proportion of participants in each accuracy level, colored by reference class. A larger % of participants in the Exact Match, or 0.01-2% error bins indicates better performance.

We next categorized responses into four accuracy levels (exact match [0% error], minor deviations [0.01–2%], moderate deviations [2.01–15%], and major deviations [>15%]) for our primary statistical modeling. Using Bayesian ordinal regression, we modeled the ordered accuracy outcome as a function of the reference class condition, while controlling for random variation across participants and family scenarios:

$$\text{Accuracy Level} \sim \text{Reference Class} + \text{Calculator} + (1|\text{id}) + (1|\text{Family Scenario})$$

This approach allowed us to estimate thresholds (intercepts) and regression coefficients that capture how different reference classes affect the likelihood of achieving higher accuracy categories. For each comparison, we provide posterior odds ratios (OR) and their 95% CIs. This approach allows the estimation of threshold parameters and regression coefficients that characterize how changes in predictor variables (such as the reference class: kWh, percentage, or USD) relate to probabilities of being in each accuracy category.

Table 3: **Experiment 1**: Ordinal Regression results. Ordinal regression results. Positive coefficients for the reference class predictors indicate that those conditions are associated with higher error categories relative to the kWh baseline.

Parameter	Estimate	CI_Lower	CI_Upper	pd
Intercept[1]	-3.8	-5.45	-2.28	1.00
Intercept[2]	-1.7	-3.29	-0.15	0.98
Intercept[3]	2.8	1.27	4.40	1.00
refClassPercentage	1.3	0.01	2.66	0.98
refClassUSD	2.8	1.52	4.04	1.00
calcUsedCalculator	-2.8	-4.09	-1.56	1.00

Table 4: **Experiment 1**: Odds ratios for group comparisons. Odds ratios greater than 1 indicate increased odds of falling into a worse accuracy category compared to the kWh condition.

Comparison	odds_ratio	ci_lower	ci_upper
Percentage vs kWh	3.7	1.0	14
USD vs kWh	15.7	4.6	57

As shown in Table 3, the reference class coefficients are positive for both the Percentage (Estimate = 1.3, 95% CI: 0.01 to 2.66, pd = 0.98) and USD (Estimate = 2.8, 95% CI: 1.52 to 4.04, pd = 1.00) conditions, relative to the kWh baseline. This indicates that, compared to the kWh condition, participants in both the Percentage and USD conditions were more likely to produce plans that fell into higher error categories. Moreover, the odds ratios (see Table 3) suggest that the USD condition led to a notably higher likelihood of large errors compared to the kWh baseline (OR = 15.7), while the Percentage condition also demonstrated increased odds (OR = 3.7) but was somewhat less detrimental to accuracy than USD. These results align with our descriptive findings and further clarify that framing the target reductions in absolute kWh units may facilitate significantly more accurate planning. Posterior predictive checks showed that the ordinal model provided a reasonable fit to the observed data (see Figure 4).

To further investigate individual factors that may influence planning accuracy, we examined the relationship between participants' energy literacy scores and their performance on the task. Energy literacy was assessed using an 8-item questionnaire adapted from (DeWaters & Powers, 2011), which covers topics such as energy units, appliance energy consumption, and sources of electricity. A Bayesian linear regression model was fit with log-transformed absolute

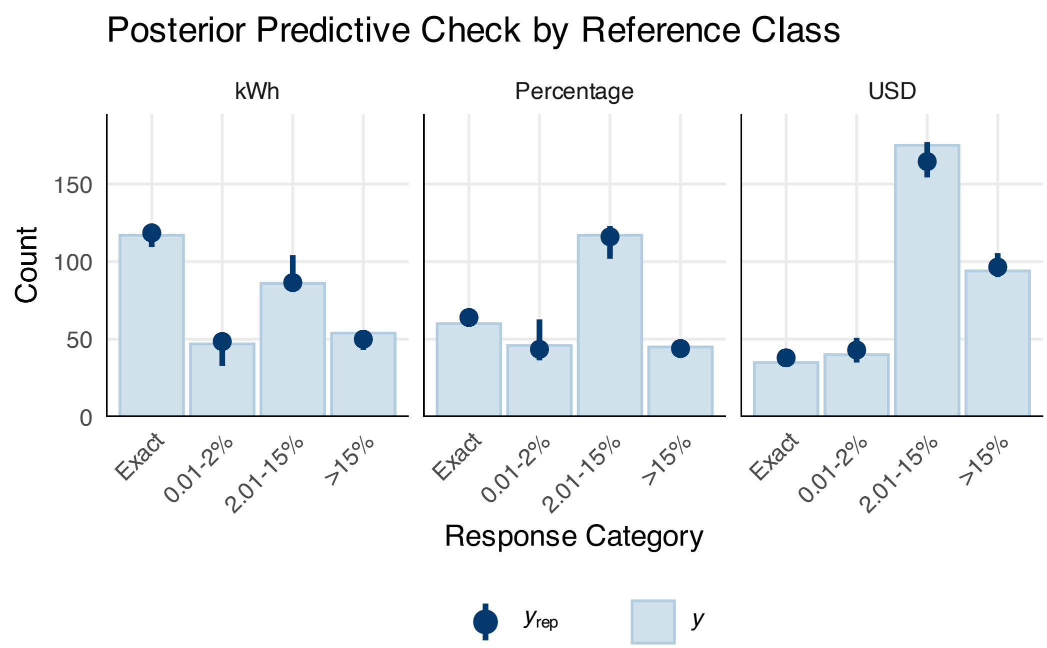

Figure 4: Study 1: Proportion of participants in each accuracy level, colored by reference class, and seprated in facets based on the levels of reduction goal. A larger % of participants in the Exact Match, or 0.01-2% error bins indicates better performance.

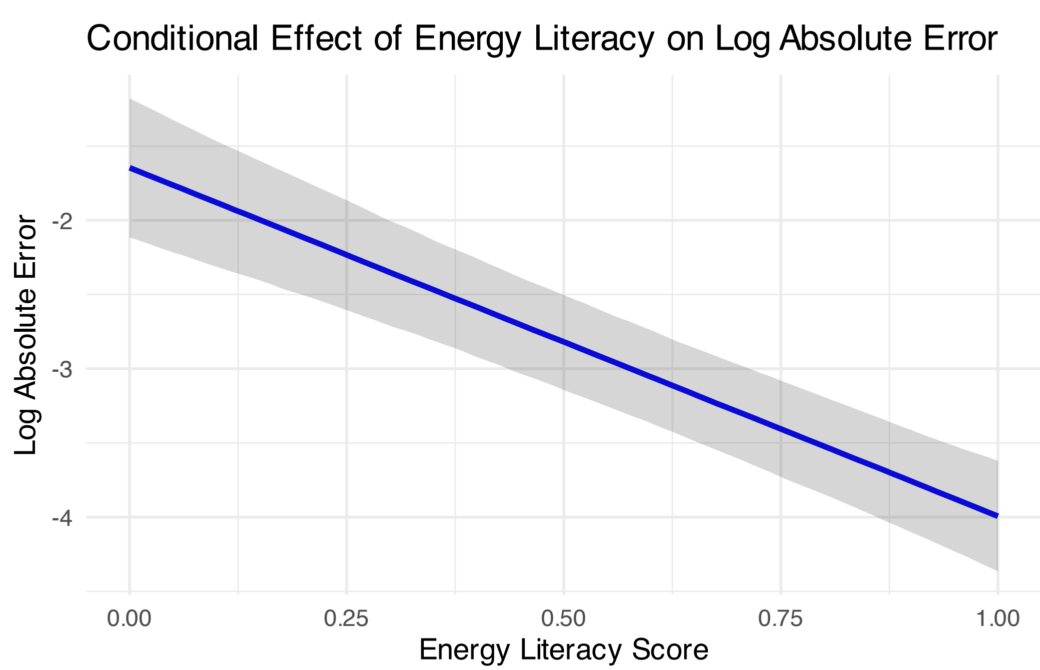

Figure 5

error as the outcome variable and energy literacy score as the predictor, controlling for random effects of participant and state: log_abs_error ~ els + (1|id) + (1|state). Results indicated a significant negative relationship between energy literacy and log absolute error (Estimate = -2.35, 95% CI: -2.88 to -1.81), suggesting that participants with higher energy literacy scores tended to have smaller deviations from the target reduction goal, and thus more accurate plans overall (Figure 5).

Experiment 1: Discussion

Experiment 1 examined how different numerical representations of energy reduction goals influenced participants' planning accuracy. In line with our hypothesis that absolute units would yield better accuracy, the kWh condition supported significantly more precise energy reduction plans than did either the Percentage or USD conditions. Although the Percentage format was detrimental to accuracy relative to kWh, it was the USD condition that consistently produced the poorest outcomes, suggesting that monetary terms, while intuitive in everyday contexts, may not serve as effective reference classes for planning appliance-specific reductions in energy use.

Experiment 2 will extend these findings by examining whether additional variables, such as the difficulty of the reduction goal or the rounding of numerical values, further interact with reference class conditions, thereby providing a more comprehensive understanding of how to optimize energy information presentation for improved planning accuracy.

Experiment 2

Methods

The experimental procedures in study 2 are quite similar to those in study 1, but we also included a rounding manipulation (rounded vs. not rounded), and a manipulation of the goal (10%

reduction vs. 15% rediction). We recruited 206 participants from Amazon Mechanical Turk, but data from from 10 participants were corrupted due to experimenter error, leaving a final sample of 196 participants.

Note that reference class remains a between-subjects variable, while percent goal, rounding, and state are within-subjects variables. In study 2, the new design is a 4 state temperature (2 warm vs. 2 cold states) X 2 task goal (10% vs. 15%) X 2 last year's usage for the family and the state average (exact vs. rounded numbers) within X 3 task reference class (USD vs. Percentage vs. kWh) between.

Results

Table 5: Study 2: Summary of planning accuracy by reference class. The table shows performance as both the % of trials where participants matched the goal, and the mean absolute error from the target reduction goal

Reference Class	% meeting goal (exact)	% meeting goal (close match)	Abs. Deviation	Log Abs. Deviation
kWh	0.44	0.52	0.02	-3.9
Percentage	0.28	0.42	0.06	-3.2
USD	0.20	0.29	0.10	-2.4

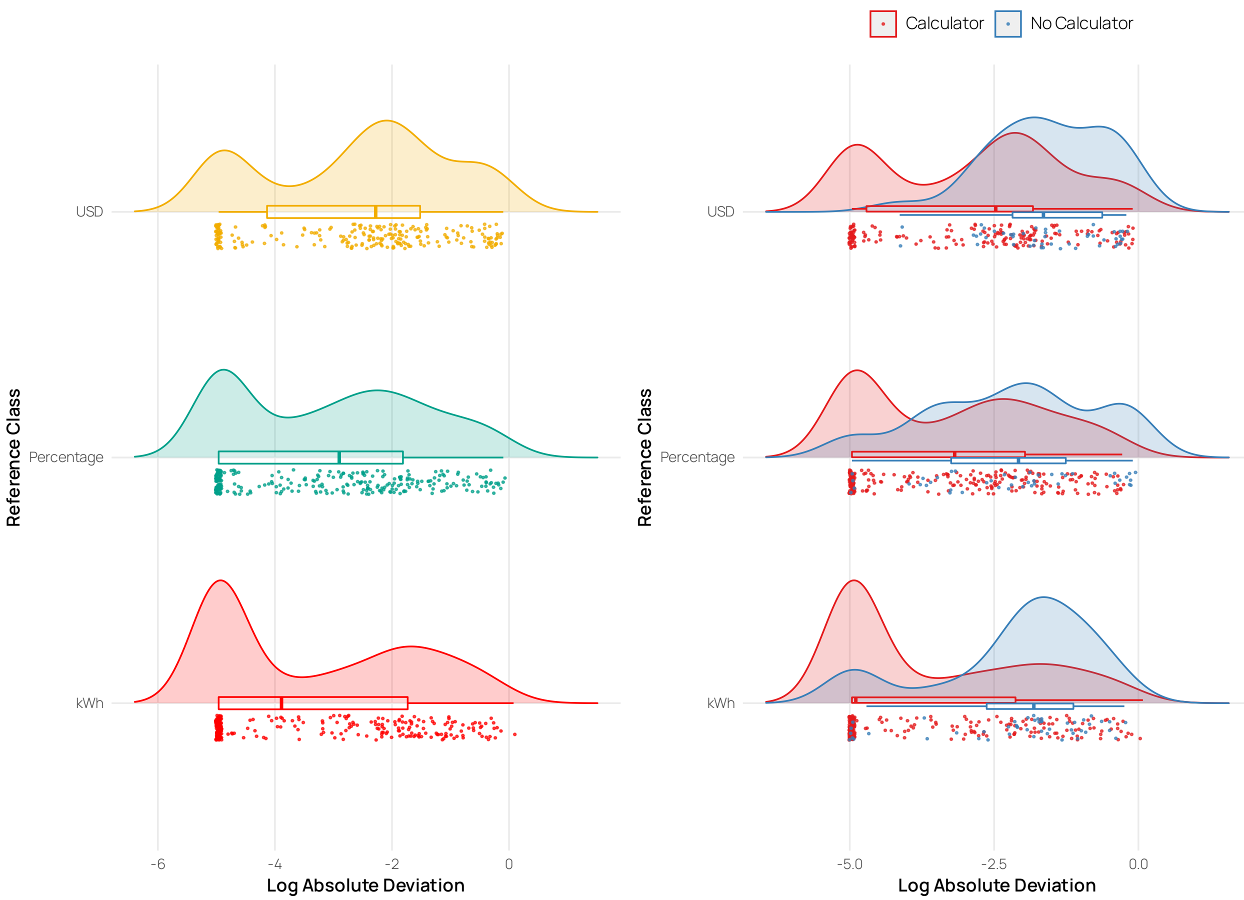

Figure 6: Study 1: Distribution of log absolute error by reference class.

Table 6: Study 2: The table shows the percentage of participants who fell into each accuracy level for each reference class condition (percentages of kWh, $, and USD columns reflect within condition percentages). The combined group column reflects the percentage of participants in each accuracy level when aggregating across across all reference class conditions.

Accuracy Level	kWh	Percentage	USD	Combined Groups %
Exact match	43.5%	26.8%	18.5%	30.2%
0.01-2% error	8%	13.8%	9.1%	10.3%
2.01-15% error	21%	33.3%	38.4%	30.5%
Over 15% error	27.5%	26.1%	34.1%	29%

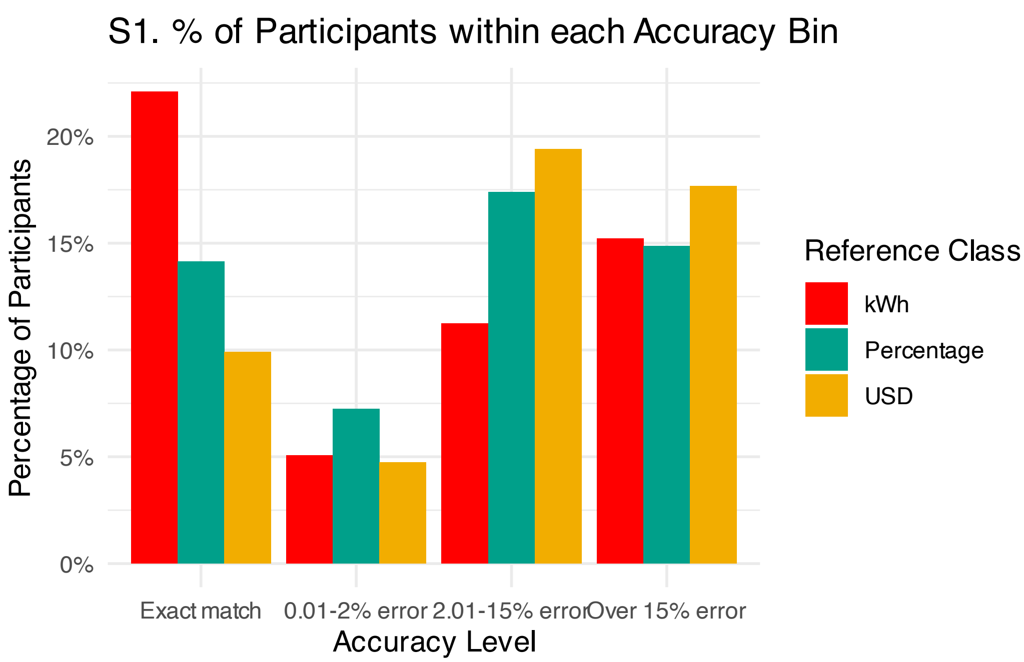

Figure 7

Table 6 shows that, once again, participants in the kWh condition achieved closer alignment with the target goals (44% exact matches), followed by Percentage (27%) and USD (18%). These percentages are consistent with the patterns observed in Study 1, reinforcing the conclusion that providing goals in kWh supports better accuracy.

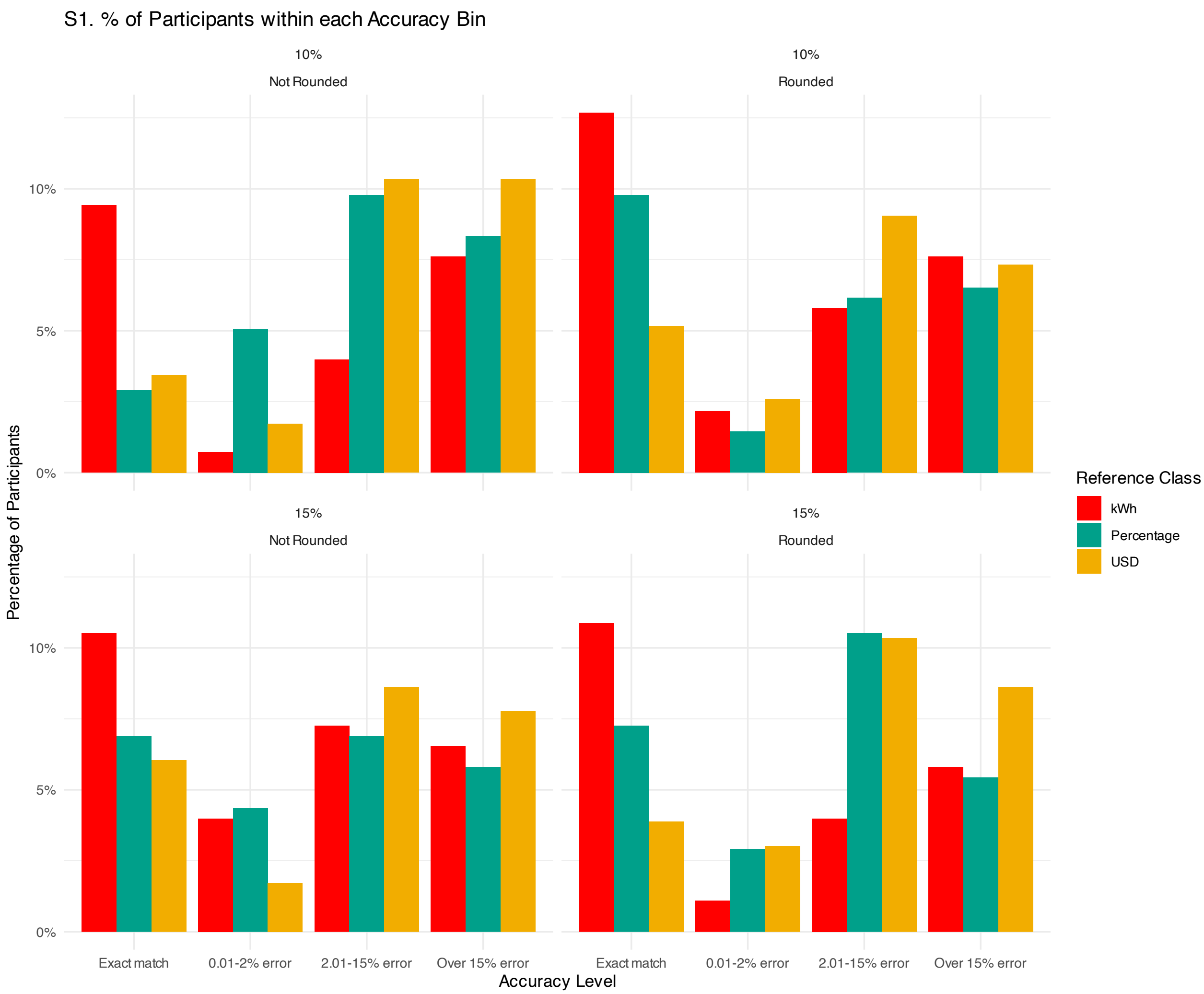

Figure 8: Study 2: Proportion of participants in each accuracy level, colored by reference class, and seprated in facets based on the levels of reduction goal, and rounding. A larger % of participants in the Exact Match, or 0.01-2% error bins indicates better performance.

comparison	odds_ratio	ci_lower	ci_upper
Percentage vs kWh	2.29	0.53	10.31
USD vs kWh	6.49	1.37	28.42
Rounded vs Not	0.52	0.36	0.73
15% Goal vs 10% Goal	0.65	0.45	0.91

Table 8: **Experiment 2.** Ordinal Regression Model Results.

Parameter	Estimate	CI_Lower	CI_Upper	pd
Intercept[1]	-2.13	-3.39	-0.86	1.00
Intercept[2]	-0.62	-1.89	0.63	0.84
Intercept[3]	3.15	1.88	4.42	1.00
refClassPercentage	0.83	-0.64	2.33	0.87
refClassUSD	1.87	0.31	3.35	0.99
roundedRounded	-0.66	-1.01	-0.31	1.00
pct_goal15%	-0.44	-0.79	-0.10	0.99

Table 9: **Experiment 2.** Odds ratios for group comparisons.

comparison	odds_ratio	ci_lower	ci_upper
Percentage vs kWh	3.02	0.53	10.31
USD vs kWh	8.80	1.37	28.42
Rounded vs Not	0.53	0.36	0.73

comparison	odds_ratio	ci_lower	ci_upper
15% Goal vs 10% Goal	0.66	0.45	0.91

We again employed Bayesian ordinal logistic regression to model the probability of participants falling into each accuracy category as a function of reference class, rounding, and goal level (Table 9 and Table 8). Results indicated that the kWh condition served as a baseline for higher accuracy. Compared to kWh, the USD reference class increased the odds of falling into lower-accuracy bins (Odds Ratio = 8.80, 95% CI: 1.37 to 28.42). The Percentage condition showed a similar trend, though the credible intervals were more uncertain. Notably, the "Rounded" condition showed an advantage: rounded usage information reduced the likelihood of errors (OR = 0.53, 95% CI: 0.36 to 0.73). Moreover, when the goal was more challenging (15% vs. 10%), accuracy generally declined (OR = 0.66, 95% CI: 0.45 to 0.91). Thus, while rounding facilitated more accurate responses, the more difficult goal reduced overall accuracy. Crucially, the kWh condition's advantage persisted across these additional manipulations, reinforcing the conclusion from Experiment 1 that absolute units support better accuracy in energy reduction planning.

As in Experiment 1, we further investigated the role of individual differences in energy literacy in predicting planning accuracy. A Bayesian linear regression model, analogous to the one used in Experiment 1 (log_abs_error ~ els + (1|id) + (1|state)), revealed a significant negative relationship between energy literacy scores and log-transformed absolute error (Estimate = -3.21, 95% CI: -3.89 to -2.52). This finding indicates that participants with higher energy literacy tended to produce more accurate plans, exhibiting smaller deviations from the target reduction goals. The conditional effect plot (Figure 10) visually confirms this relationship, showing a clear

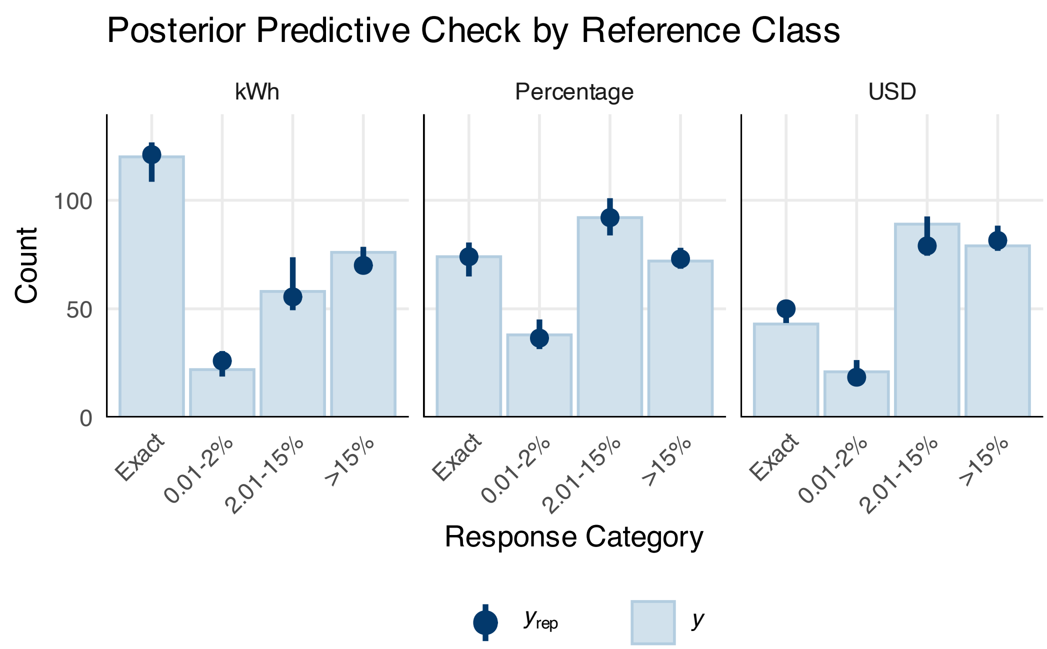

Figure 9

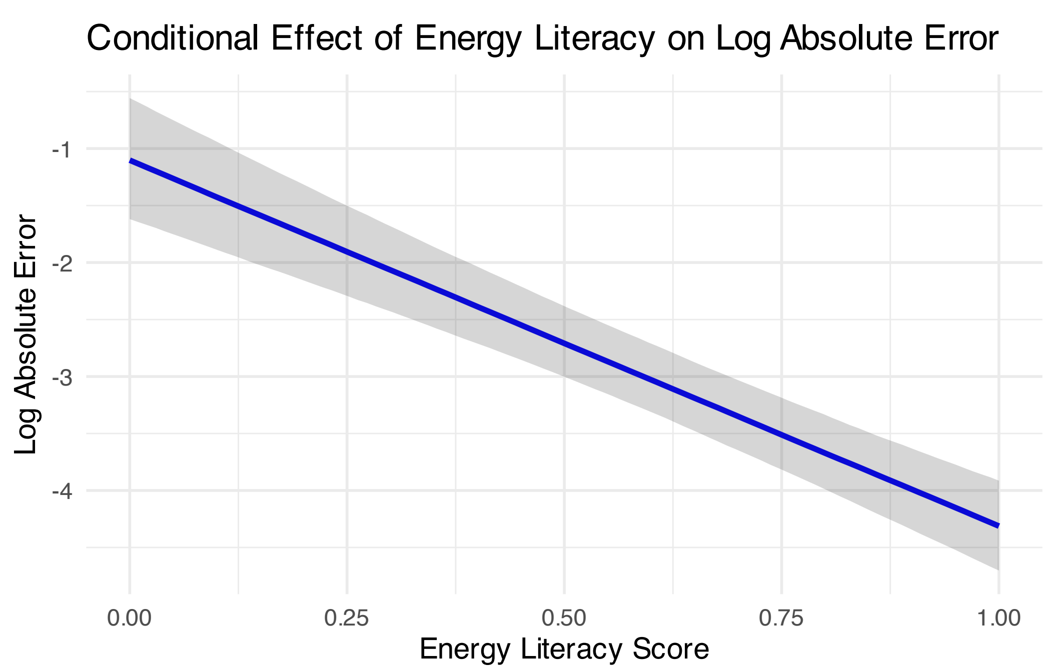

Figure 10

decreasing trend in log absolute error as energy literacy increases. These results are consistent with the findings from Experiment 1 and further support the notion that a solid understanding of energy concepts may be crucial for individuals' ability to effectively engage in energy conservation planning. Furthermore, these findings highlight the potential value of targeted educational interventions aimed at improving consumers' energy literacy to enhance the effectiveness of communications promoting sustainable energy behaviors.

Experiment 2: Discussion

Individual Differences

General Discusion

Karjalainen 2011 - people prefer information about price (Karjalainen, 2011)

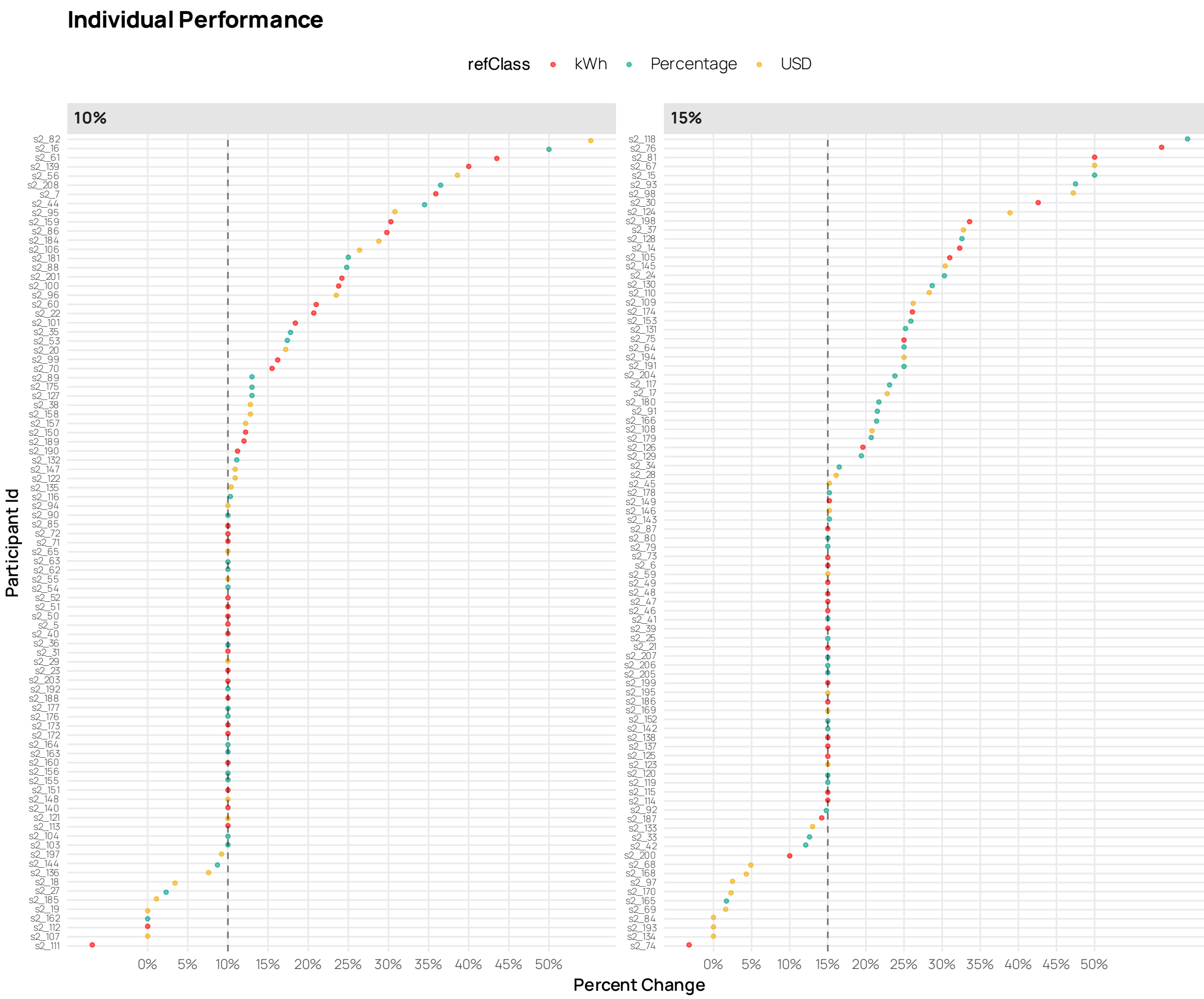

Figure 11: Study 2: Individual performance in the energy planning task, colored by reference class. The dashed line represents the target reduction goal. Participants are shown along the y axis, those who fall above or below the dashed line have not met the target goal. The x-axis represents the percent change in energy usage from the prior year.

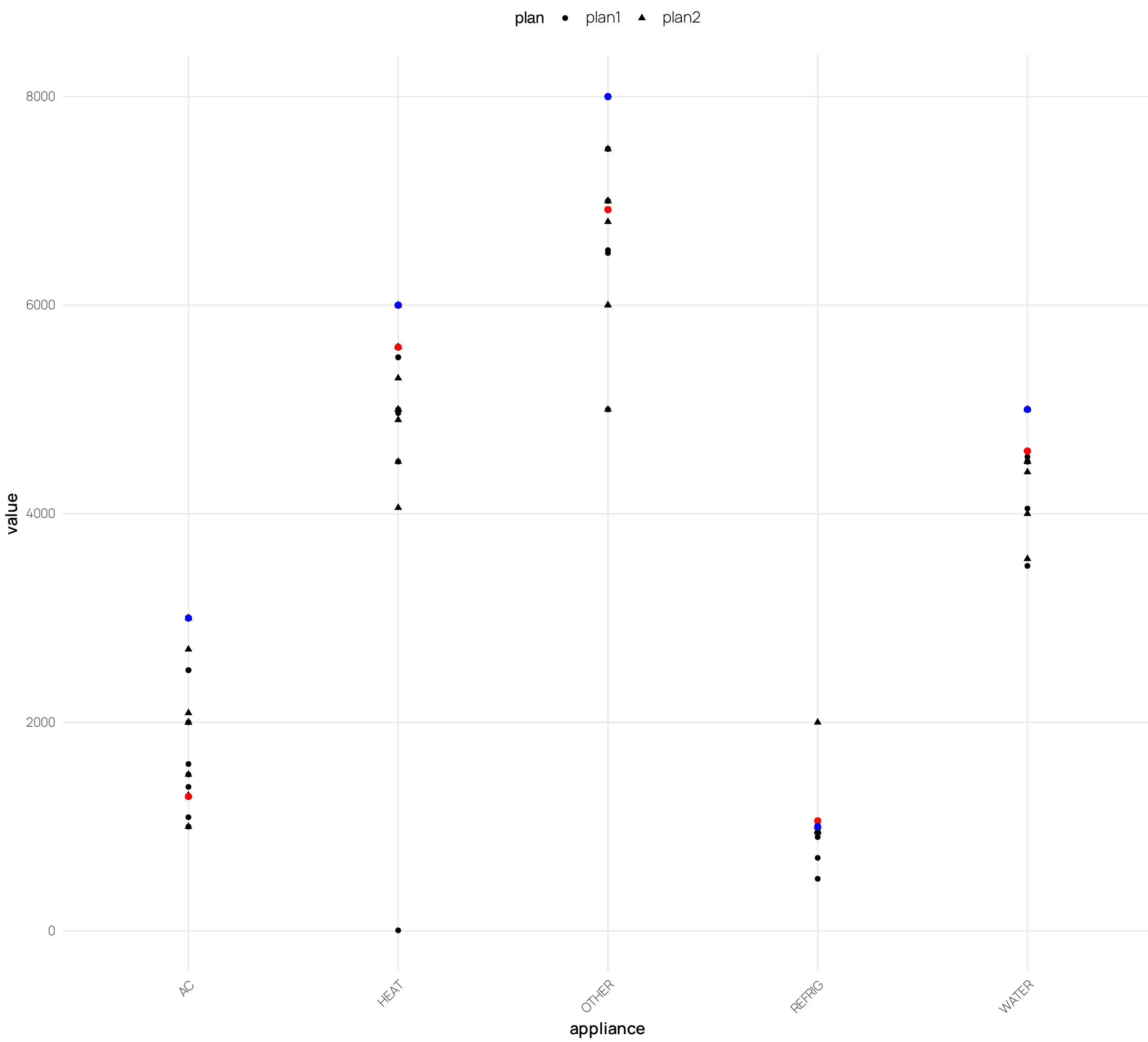

Figure 12: Study 2: Respones patterns for a subset of individiual participants. Black points are participant responses, red points are the state average, and blue points are the family average. The x-axis represents the appliance category, and the y-axis represents the energy usage in kWh.

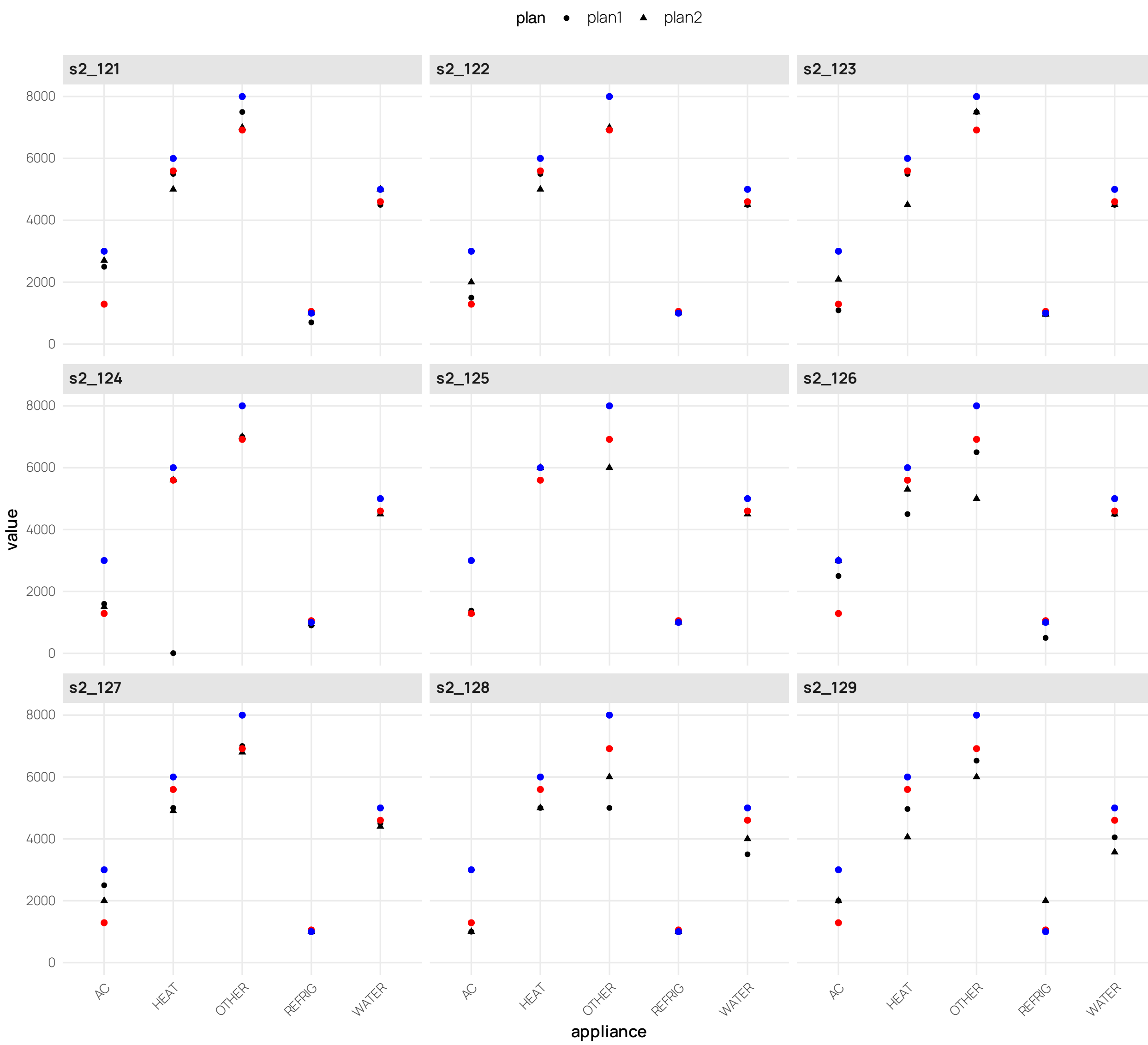

Figure 13: Study 2: Respones patterns for a subset of individiual participants. Black points are participant responses, red points are the state average, and blue points are the family average. The x-axis represents the appliance category, and the y-axis represents the energy usage in kWh.

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