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

- Canfield et al. (2017) found that tables were more effective than graphs for conveying specific electricity usage data, likely because tables facilitate straightforward point reading. However, they also noted that individuals with lower energy literacy had reduced comprehension across all formats.
- Canfield et al. (2017)'s findings on preferences for historical use information and the impact of neighbor comparisons
- The concept of cognitive fit posits that performance improves when the information presentation format aligns with the task requirements (Vessey, 1991)
- alignment can reduce cognitive load and enhance accuracy in planning (Shah & Freedman, 2011)
- Reimer et al. (2015) provide context on how numerical formats affect risk perception, the reference class problem, and the benefits of natural frequencies.

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.

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 intially 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 an other appliances (e.g., TV, lighting).

For each family scenario, the particpipants 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.

Additional data collected included:

- **Energy Literacy Quiz**: An 8-item questionnaire assessing participants' knowledge of energy consumption and conversion.
- **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.

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)

- **Environmental Attitudes Survey**: Assessed participants' pro-environmental attitudes and perceived importance of energy conservation.

Results

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.

refClass	Avg. % meeting goal	Avg. Deviation From Goal
kWh	0.38	0.15
Percentage	0.22	0.16
USD	0.10	0.19

For our primary analyses of participants' ability to create accurate energy-saving plans, we employed an accuracy level binning approach by categorizing responses into four distinct levels: Exact match, 0.01–2% error, 2.01–15% error, and Over 15% error. The current analysis employs a cumulative ordinal regression model, implemented via a Bayesian hierarchical framework (Bürkner, 2017) . 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. All analyses were carried out in R (Team, 2020) and the tidyverse package (Wickham et al., 2019).

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	26.3%	41.9%	47.8%	38.9%
Over 15% error	21.2%	18.4%	31.2%	24.1%

see Figure 2

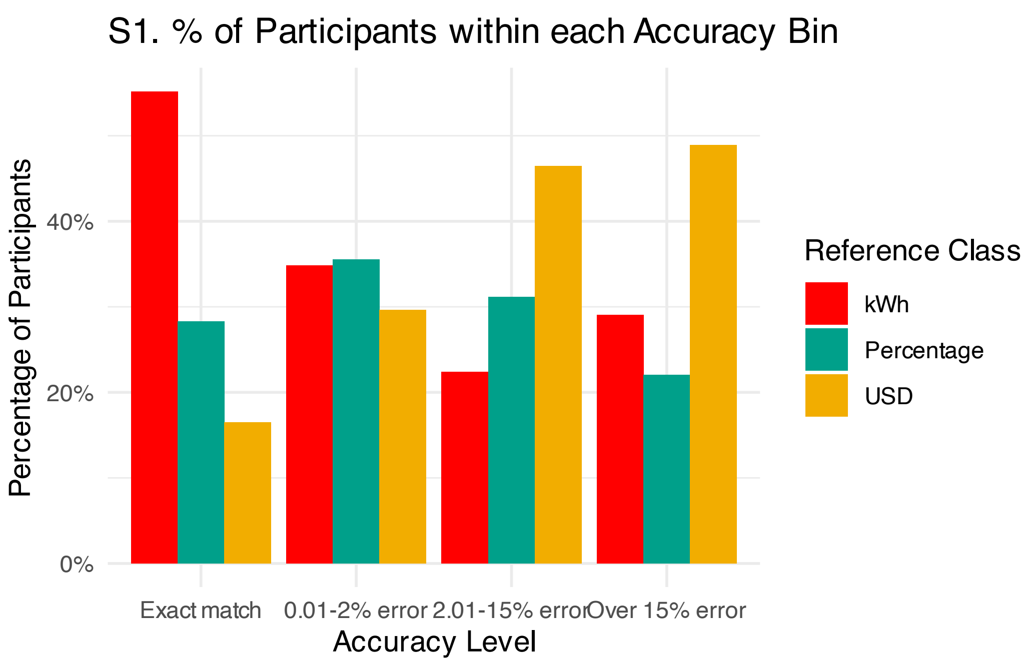

Figure 2: Study 1: Proportion of participants in each accuracy level, colored by reference class. A larger % of participants in the Exact Match, or 0.01-2% error bins indicates better performance.

We analyzed planning accuracy using Bayesian ordinal regression. The dependent variable, plan error, was computed by binning the goal deviation into four ordered levels: exact match

(0% error), minor deviations (0.01-2% error), moderate deviations (2.01-15% error), and major deviations (>15% error). For each comparison, we provide posterior odds ratios (OR) and their 95% CIs.

Table 3: **Experiment 1**: Ordinal Regression results.

Parameter	Estimate	CI_Lower	CI_Upper	pd
Intercept[1]	-1.94	-3.19	-0.74	1.00
Intercept[2]	0.20	-1.02	1.42	0.63
Intercept[3]	4.36	3.11	5.65	1.00
refClassPercentage	0.85	-0.54	2.23	0.88
refClassUSD	2.72	1.41	4.06	1.00

Table 4: **Experiment 1**: Odds ratios for group comparisons.

Term	Estimate	Est.Error	Q2.5	Q97.5
refClassPercentage	2.3	2	0.58	9.3
refClassUSD	15.2	2	4.11	58.1

The ordinal model is parameterized with thresholds (intercepts), and positive coefficients can indicate that it is more difficult to achieve higher accuracy categories in the USD condition. The model output suggests that, compared to the kWh condition, the USD condition shows a positive coefficient (Estimate = 2.72, 95% CI: 1.41 to 4.06) for the ordinal outcome. At least to me, this positive coefficient appears to indicate that, relative to the kWh reference class, participants in the USD condition are more likely to fall into higher numerical categories of the dependent variable coding. However, because the dependent variable is ordered from best (Exact match) to worst (Over 15% error), care is needed in interpretation. The Percentage condition coefficient (Estimate = 0.85, 95% CI: -0.54 to 2.23) is more uncertain, with its credible interval overlapping zero. Posterior predictive checks (Figure 3) showed that the ordinal model provided a reasonable fit to the observed data (see Figure 3).

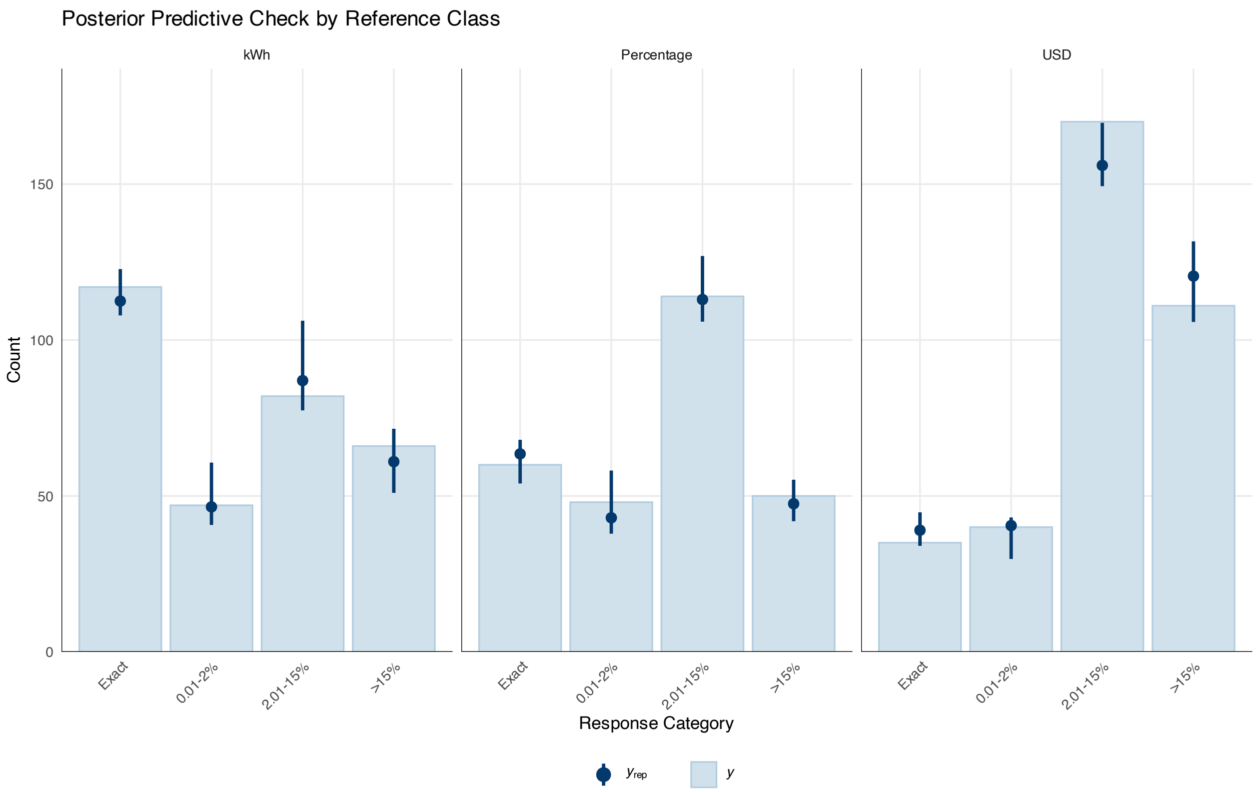

Figure 3: Study 1: Proportion of participants in each accuracy level, colored by reference class, and seprated in facets based on the levels of reduction goal. A larger % of participants in the Exact Match, or 0.01-2% error bins indicates better performance.

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.

refClass	Avg. % meeting goal	Avg. Abs. Deviation From Goal	Log Deviation
kWh	0.44	0.13	-4.7
Percentage	0.27	0.16	-3.5
USD	0.18	0.17	-2.5

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%

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 %
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%

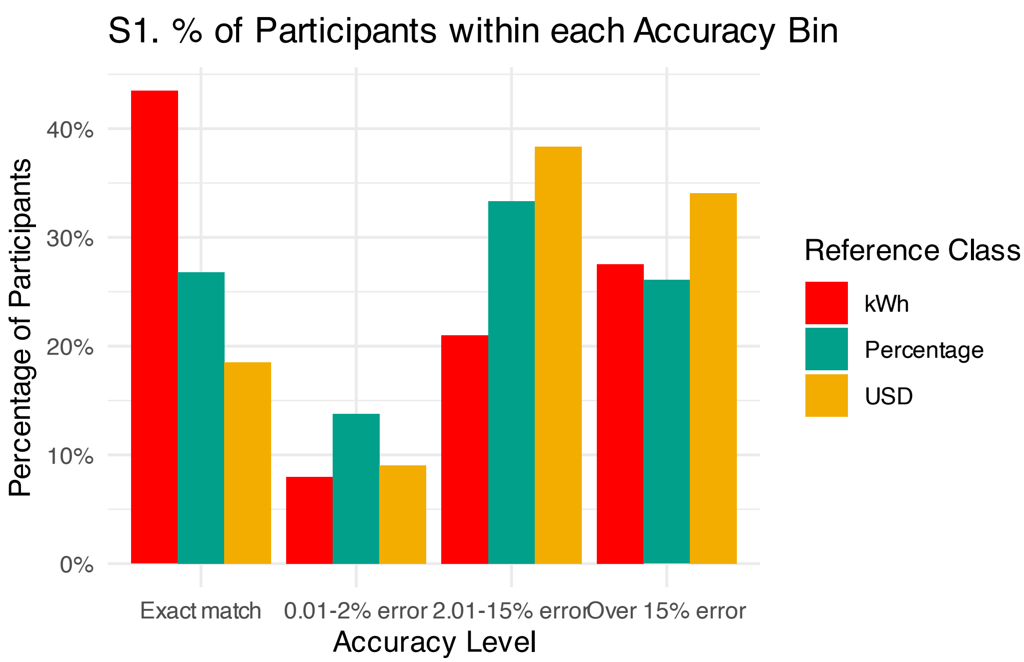

Figure 4

Table 7: **Experiment 2.** Ordinal Regression Model Results.

Parameter	Estimate	CI_Lower	CI_Upper	pd
Intercept[1]	-2.13	-3.39	-0.86	1.00

Parameter	Estimate	CI_Lower	CI_Upper	pd
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 8: **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
15% Goal vs 10% Goal	0.66	0.45	0.91

Individual Differences

see Figure 7

Discusion

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

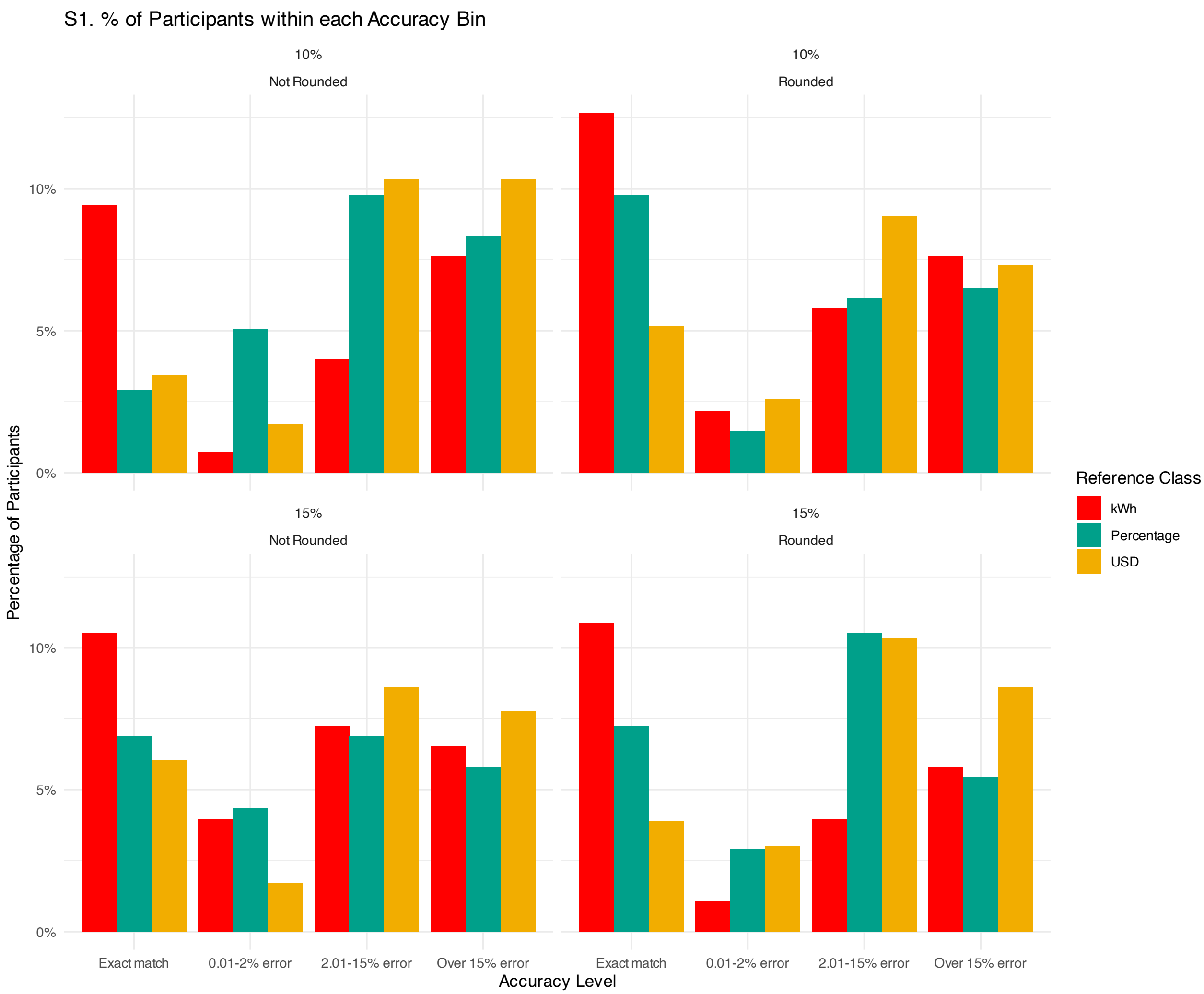

Figure 5: Study 2: Proportion of participants in each accuracy level, colored by reference class, and seprated in facets based on the levels of reduction goal, and rounding. A larger % of participants in the Exact Match, or 0.01-2% error bins indicates better performance.

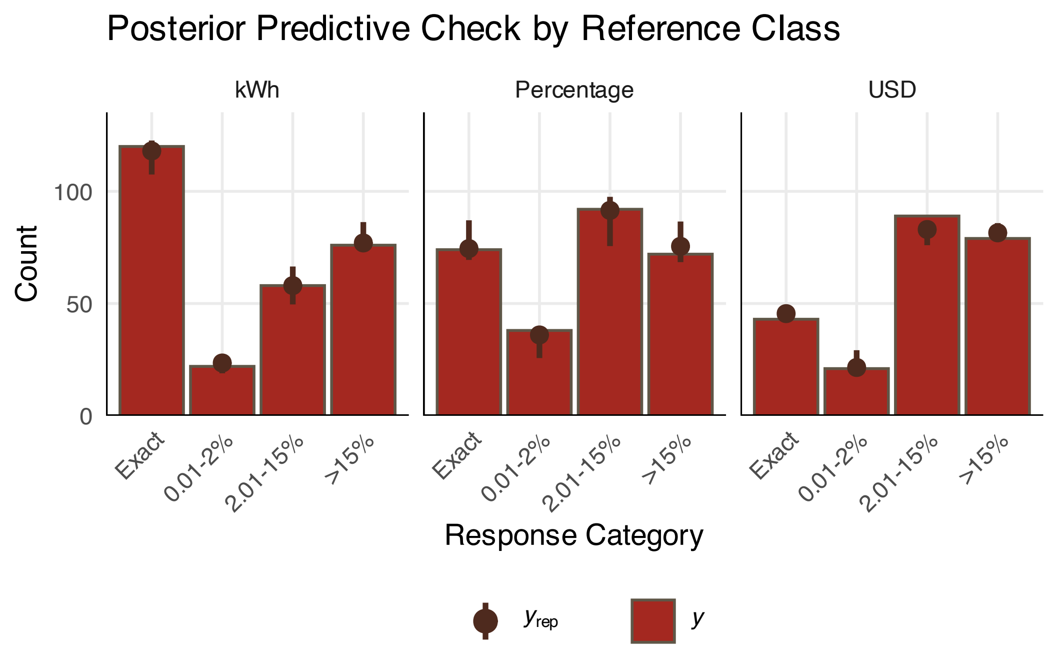

Figure 6

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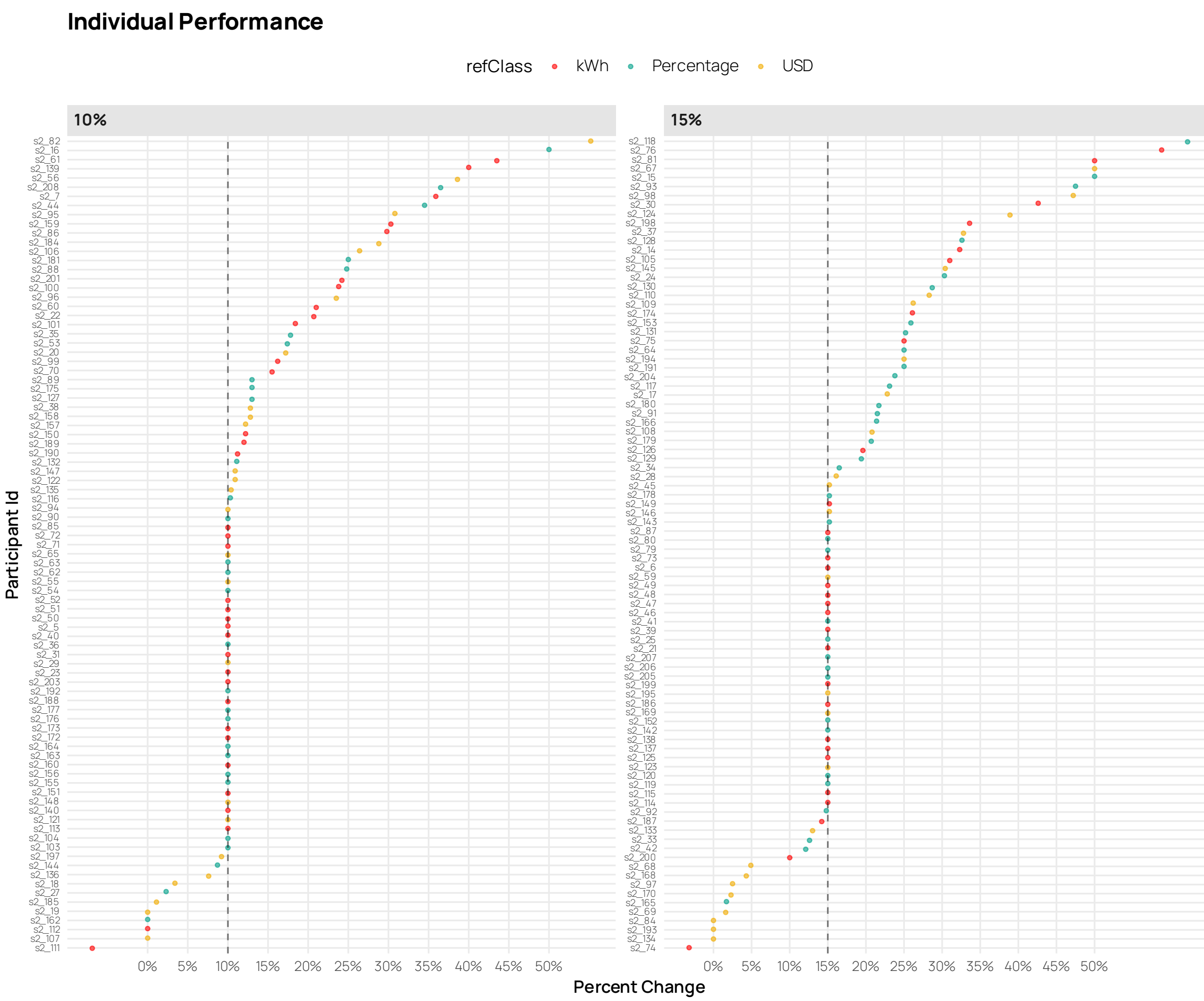

Figure 7: Study 2: Individual performance in the energy planning task, colored by reference class. The dashed line represents the target reduction goal. Participants are shown along the y axis, those who fall above or below the dashed line have not met the target goal. The x-axis represents the percent change in energy usage from the prior year.

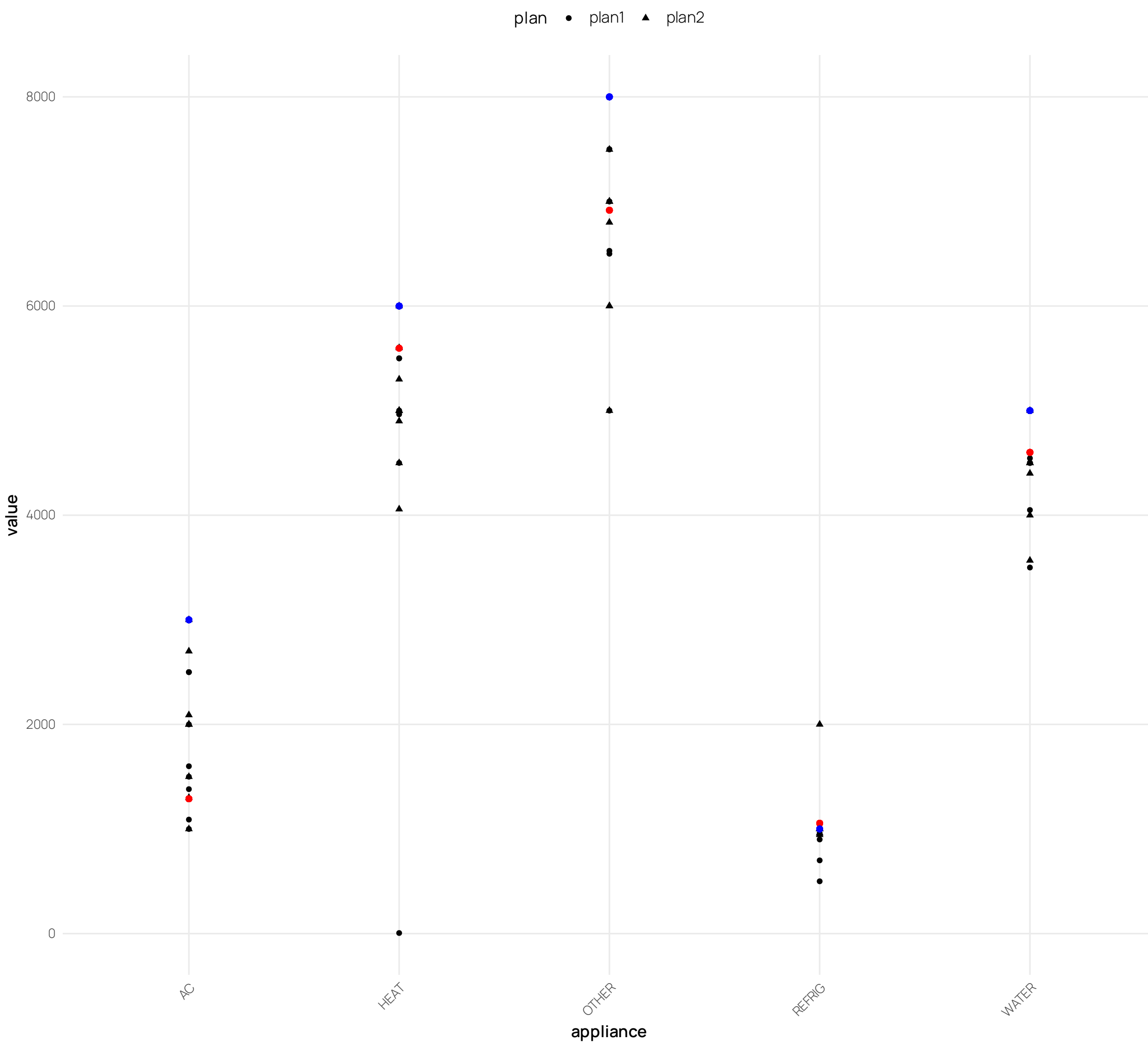

Figure 8: Study 2: Respones patterns for a subset of individiual participants. Black points are participant responses, red points are the state average, and blue points are the family average. The x-axis represents the appliance category, and the y-axis represents the energy usage in kWh.

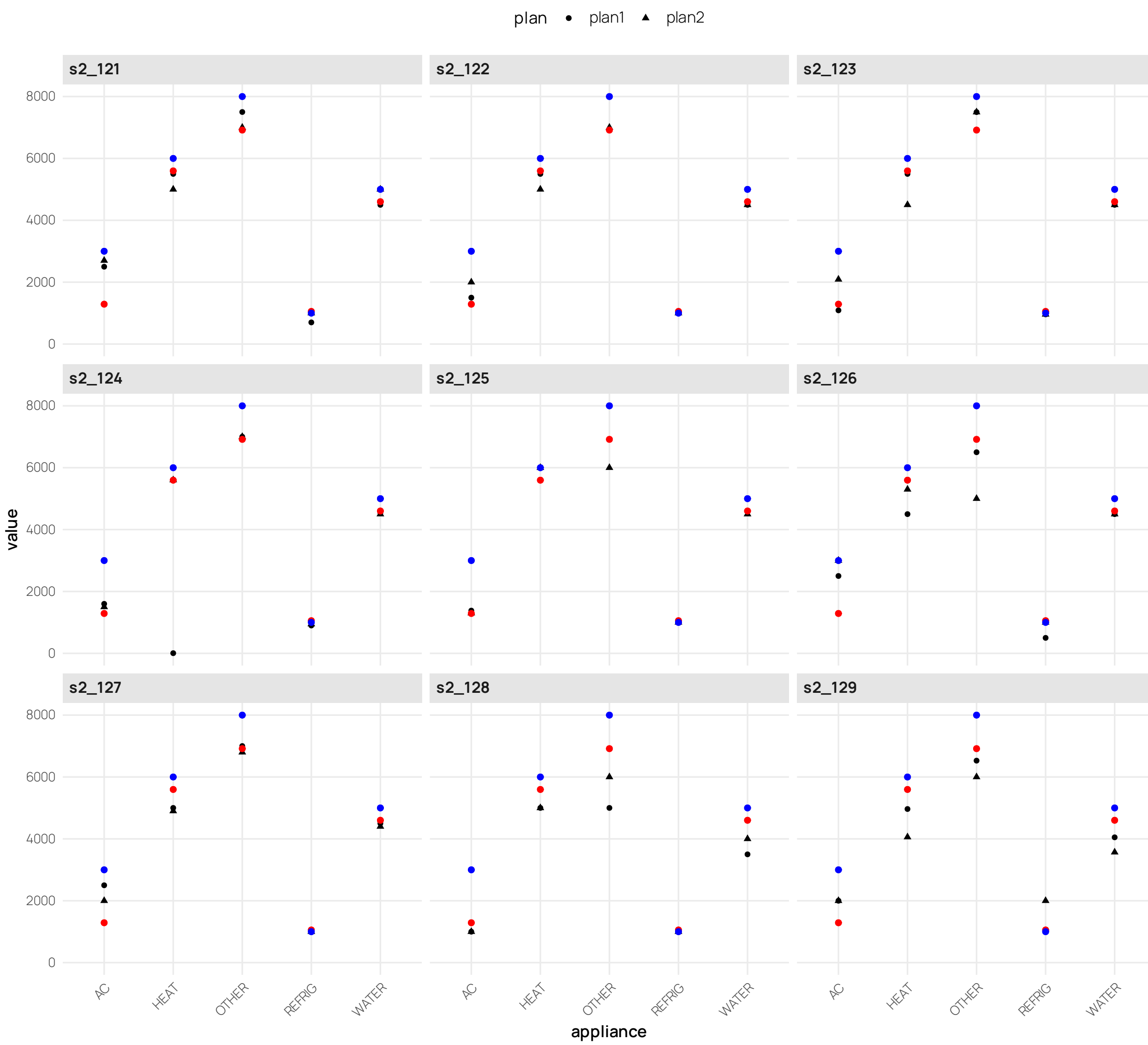

Figure 9: Study 2: Respones patterns for a subset of individiual participants. Black points are participant responses, red points are the state average, and blue points are the family average. The x-axis represents the appliance category, and the y-axis represents the energy usage in kWh.

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