Energy_Appliance

Sunday, May 4, 2025 1:07 PM

Attari, S. Z., & Rajagopal, D. (2015). Enabling energy conservation through effective decision aids. *Journal of Sustainability Education*, *8*, 1–15.

Table 1. A non-exhaustive list of various daily activities that involve an individual directly consuming energy.

Home related activities	**Appliance examples**	**Fuel choice**
Space cooling	Air-conditioning (central or window unit)	Electricity*
Space heating	Furnace or Heat Pump	Electricity, Gas, Oil
Water services	Water heater, Faucets, Toilets, Swimming pool	Electricity (for heaters), Gas
Food storage	Refrigerator	Electricity
Food preparation	Stove, Oven	Electricity, Gas
Lighting	LED, CFL, Incandescent bulb	Electricity
Cleaning	Dishwasher, Clothes Washer, Dryer	Electricity, Gas (for dryer)
Communications and Entertainment	Computers, Phone, Television, Printers, Cable box	Electricity
Indoor Recreation	Exercise equipment	Electricity
Outdoor maintenance	Lawnmower	Gasoline, Diesel
Transport related activities	**Travel mode examples**	**Fuel choice**
Commuting to work	Walk, Bicycle, Motorbike, Train, Bus, Carpool, Automobile, Telecommute	Gasoline, Diesel, Biofuel (for personal automobiles only)
Leisure travel**	All above plus air travel with telecommute excluded	All above + Jet fuel (for air travel)

* Choice with respect to electricity is in the form of an option available to most consumers to purchase any given share of their electricity from renewable sources.
** Although leisure travel and some residential activities may in reality occur occasionally, one could derive average daily energy consumption for each activity.

A brief overview of existing decision aids

We use the term "decision aid" to refer to any information that a consumer can access to help them make decisions about energy use. Some decision aids simply provide a list of presumed effective behaviors for people to incorporate into their lives, without providing

Attari, S. Z., DeKay, M. L., Davidson, C. I., & Bruine De Bruin, W. (2010). Public perceptions of energy consumption and savings. *Proceedings of the National Academy of Sciences*, *107*(37), 16054–16059.
https://doi.org/10.1073/pnas.1001509107
https://www.pnas.org/action/downloadSupplement?doi=10.1073%2Fpnas.1001509107&file=sapp.pdf

Public perceptions of energy consumption and savings

Shahzeen Z. Attari[a,1], Michael L. DeKay[b], Cliff I. Davidson[c,d,2], and Wändi Bruine de Bruin[c,e]

[a]The Earth Institute and Center for Research on Environmental Decisions, Columbia University, New York, NY 10027; [b]Department of Psychology, Ohio State University, Columbus, OH 43210; and Departments of [c]Engineering and Public Policy, [d]Civil and Environmental Engineering, and [e]Social and Decision Sciences, Carnegie Mellon University, Pittsburgh, PA 15213

Edited by William C. Clark, Harvard University, Cambridge, MA, and approved July 12, 2010 (received for review February 12, 2010)

In a national online survey, 505 participants reported their perceptions of energy consumption and savings for a variety of household, transportation, and recycling activities. When asked for the most effective strategy they could implement to conserve energy, most participants mentioned curtailment (e.g., turning off lights, driving less) rather than efficiency improvements (e.g., installing more efficient light bulbs and appliances), in contrast to experts' recommendations. For a sample of 15 activities, participants underestimated energy use and savings by a factor of 2.8 on average, with small overestimates for low-energy activities and large underestimates for high-energy activities. Additional estimation and ranking tasks also yielded relatively flat functions for perceived energy use and savings. Across several tasks, participants with higher numeracy scores and stronger proenvironmental attitudes had more accurate perceptions. The serious deficiencies highlighted by these results suggest that well-designed efforts to improve the public's understanding of energy use and savings could pay large dividends.

climate change | decision making | judgment | environmental behavior | anchoring

involved in climate change (8, 9) and of the energy consumption associated with familiar activities, even though the public may believe that climate change is real (10). For example, Larrick and Soll (11) reported that people in the United States mistakenly believe that gasoline consumption decreases linearly rather than nonlinearly as an automobile's gas mileage (in miles per gallon) increases. Describing vehicles' fuel efficiency in terms of "gallons per 100 miles" corrected this misperception and led to more fuel-efficient choices. The authors therefore recommended that the United States switch to the latter metric.

Demand-side policy responses to climate change, such as encouraging consumers to adopt more efficient technologies, would benefit from a better understanding of how much individuals know about energy consumption in situations in which they have some direct control. In this study, we investigated public perceptions of energy use and potential energy savings associated with a variety of activities, devices, and technologies, many of which were drawn from Gardner and Stern's (6) short list.

For a key portion of our study, we used the classic risk-perception research of Lichtenstein et al. (12) as a guiding analogy. Those authors asked people to estimate the number of annual

Anthropogenic CO_2 emissions are contributing to global climate change (1) and could negatively impact our way of life if serious action is further delayed. The United States produces 21% of the world's CO_2 emissions, with 98% of US emissions attributed to energy consumption (2).

According to Pacala and Socolow (3), increasing energy efficiency and curtailing activities that consume energy may be our cheapest options for stabilizing atmospheric CO_2 concentrations below a doubling of preindustrial concentrations. Following the analogy of *stabilization wedges* (3), Dietz et al. (4) devised a potential *behavioral wedge*, recommending specific behavioral changes, such as weatherization investments, to be adopted by US households to decrease their emissions. Vandenbergh et al. (5) identified seven actions, such as reducing automobile idling and substituting compact fluorescent light bulbs (CFLs) for incandescent bulbs, that have the potential to achieve large emission reductions at a low cost to the government and with a net savings

deaths in the United States from 30 causes (e.g., heart disease, tornadoes). Although participants' estimated fatality rates were positively correlated with actual fatality rates, the slope of the relationship was relatively flat, with overestimates for low risks and underestimates for high risks. The availability heuristic (13–15), a judgment process in which the frequency of an event is estimated according to the ease with which specific instances come to mind, provides one explanation for this result. Judging by availability can result in estimates that are generally accurate but with systematic overestimates for frequencies of vivid low-probability events (13, 15). A second explanation is provided by the anchoring-and-adjustment heuristic (14, 16), in which a person generates a numerical judgment by first adopting a salient reference point as a starting value and then adjusting his or her judgment in the desired direction. Adjustment is typically insufficient, leading to relative insensitivity to the magnitudes of true differences in frequency estimation tasks. Hertwig et al. (17) replicated Lichtenstein et al.'s (12) results using German fatality rates but argued that the primary pattern could be explained either by the availability

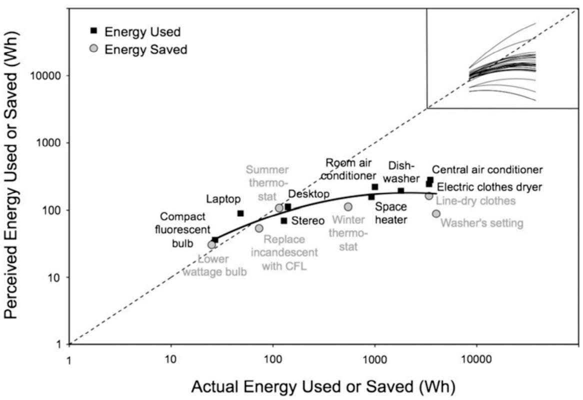


Fig. 1. Mean perceptions of energy used or saved as a function of actual energy used or saved for 15 devices and activities. Error bars for 95% confidence intervals are omitted because they are typically no taller than the symbols themselves. The diagonal dashed line represents perfect accuracy. *Inset:* Individual regression curves for 30 randomly selected participants.

lationship between participants' estimates and the actual values would be relatively flat. In addition, we expected that some individual differences, such as education, numeracy, and proenvironmental attitudes and behaviors, would be associated with more accurate perceptions of energy consumption and savings.

Results

Perceptions of the "Most Effective Thing." The study began with an open-ended survey question that asked participants to indicate the most effective thing they could do to conserve energy. Two judges identified 17 mutually exclusive categories of responses in an initial set of 40 surveys (Table 1) and then independently coded the remaining responses. Interrater agreement was "almost perfect," with $\kappa = 0.82$ (18). We further classified these categories as curtailment actions (e.g., *Turn off lights*) or efficiency actions (e.g., *Use efficient light bulbs*), although some ambiguous responses (e.g., *Conserve energy*, *Recycle*) could not be classified in this manner. Despite Gardner and Stern's (6) conclusion that efficiency-improving actions generally save more energy than curtailing the use of inefficient equipment, only 11.7% of participants mentioned efficiency improvements, whereas 55.2% mentioned curtailment as a strategy for conserving energy.

Perceptions of Energy Used and Saved. Each participant estimated the energy used by nine devices and appliances and the energy saved by six household activities, with the energy used by a 100-W incandescent light bulb in 1 h provided as a reference point. For each participant, we assessed the correlation between these perceptions and actual energy use and savings (as determined from the literature), after transforming both distributions with base-10 logarithms to reduce positive skew. The mean correlation between log10*Perception* and log10*Actual* was $r = 0.51$ [$t(488) = 36.34$, $P < 0.0001$, $\eta^2 = 0.70$], indicating that participants had significant (but imperfect) knowledge of which devices and activities were associated with greater energy use and savings.

To examine this relationship in more detail, we used the multilevel regression model (18, 19) in Eq. **1** to predict participants' perceptions of energy use and savings as a function of actual energy use and savings.

$$\begin{aligned}\log10\mathit{Perception}_{ij} &= \beta_{0j} + \beta_{1j}\log10\mathit{Actual}_i \\ &\quad + \beta_{2j}(\log10\mathit{Actual}_i)^2 + r_{ij}\end{aligned} \quad [1]$$

In this equation, i indicates the device or activity and j indicates the participant. We modeled variation among participants by letting β_{0j} and β_{1j} vary about their average values, thereby allowing each participant to have his or her own regression equation (i.e., participant j's intercept and slope differed from the average intercept and slope). In contrast, we treated the quadratic effect as fixed, so β_{2j} was the same for all participants (see *SI Text*). The functional form in Eq. **1** is the same as that used in studies of risk perception (12, 17), but we centered the values of log10*Perception* and log10*Actual* relative to the original mean of log10*Actual*, so that the coefficients would be more interpretable. The intercept β_{0j} indicates over- or underestimation, the slope β_{1j} indicates the general relationship between perceptions and actual values, and the coefficient for the quadratic term β_{2j} indicates the curvature in that relationship. This specification allows for a detailed assessment of the accuracy of participants' perceptions; for perfectly accurate perceptions, $\beta_{0j} = 0$, $\beta_{1j} = 1$, and $\beta_{2j} = 0$.

The two predictors in Eq. **1** accounted for 40% of the within-participant variation in energy perceptions (see *SI Text*). Results for the average parameter estimates are shown in Fig. 1, along with mean perceptions for the 15 devices and activities (Fig. 1 *Inset*, which highlights variation across participants, is discussed in the next section). The average intercept, which gives the average elevation of perceptions at the mean of log10*Actual*, was significantly negative [$M(\beta_{0j}) = -0.44$, $t(492) = -18.03$, $P < 0.0001$]. On average, participants underestimated energy use and savings by a factor of $10^{0.44} = 2.8$.

The average slope, evaluated at the mean of log10*Actual*, was significantly greater than zero [$M(\beta_{1j}) = 0.28$, $t(6824) = 26.91$, $P < 0.0001$] but significantly less than 1 [$t(6824) = -69.70$, $P < 0.0001$]. This gradual slope reflects two features of the data. First, it reflects the imperfect correlation between perceived and actual values. This regression toward the mean occurs whenever variables are imperfectly correlated, but it does not "explain" why the correlation is imperfect (21). Second, participants' perceptions of energy use and savings were much less variable than actual energy use and savings: The mean SD of log10*Perception*, 0.44, was approximately half that of log10*Actual*, 0.82. On average, participants demonstrated only slight sensitivity to the size of actual energy differences. For example, participants correctly reported that desktop computers consume more energy than laptop computers, but they greatly underestimated the magnitude of this difference (a perceived ratio of 1.2 rather than 2.9). This compression bias (22) is consistent with participants using the 100-Wh reference point as an anchor from which they adjusted insufficiently (15, 16).

The quadratic effect was significant and negative [$M(\beta_{2j}) = -0.19$, $t(6824) = -18.56$, $P < 0.0001$], yielding a function that is essentially flat when actual consumption and savings are high. Indeed, participants did not make accurate distinctions among large

Table 1. Categorized responses to an open-ended question about the single most effective thing that participants could do to conserve energy in their lives

Behavior category	Curtailment (C) or efficiency (E)	Percentage of participants
Turn off lights	C	19.6
Conserve energy		15.0
Drive less/bike/use public transportation	C	12.9
Change the setting on the thermostat	C	6.3
Change my lifestyle/not have children	C	5.9
Unplug appliances	C	5.7
Shut off appliances/use appliances less	C	4.9
Recycle		4.2
Other (for behaviors only mentioned once)		4.0
Education/think about my actions		3.8
Use efficient light bulbs	E	3.6
Use efficient appliances	E	3.2
Use efficient cars/hybrids	E	2.8
Sleep more/relax more		2.8
Buy green energy/solar energy/alternative energy		2.6
Insulate my home	E	2.1
There is no way/I don't know		0.8

Some behaviors could not be unambiguously classified as curtailment or efficiency.

https://www.pnas.org/action/downloadSupplement?doi=10.1073%2Fpnas.1001509107&file=pnas.201001509SI.pdf

Table S1. Data sources and values for energy use of household devices and appliances (in W)

Device or appliance	Reference					Mean
	AltE (1)		DOE (2)		Navigant (3)	
Stereo	10	30	70	400		128
Compact fluorescent light bulb (with equal brightness to a 100-W incandescent light bulb)		30			23	27
Laptop computer	20	75	50			48
Desktop computer	80	200				140
Room air conditioner		1,000				1,000
Central air conditioner	2,000	5,000				3,500
An electric clothes dryer			1,800	5,000		3,400
Dish washer			1,200	2,400		1,800
Portable heater			750	1,100		925

"Drying one load of laundry on a clothes line instead of using an electric dryer" had mean savings of 3,400 W (equivalent to not using the electric dryer).

1. Alternative Energy Store. (2008) Power ratings (typical) for common appliances. Available at http://www.altestore.com/howto/Tools-Calculators-Reference/Reference-Materials/Power-Ratings-typical-for-Common-Appliances/a21/. Accessed October 26, 2008.
2. U.S. Energy Information Administration (1992) Measuring Energy Efficiency in the United States Economy. Available at: http://www.eia.doe.gov/emeu/efficiency/eefig_ch5.htm. Accessed October 26, 2008.
3. Navigant Consulting Inc (2002) *U.S. Lighting Market Characterization (National Lighting Inventory and Energy Consumption Estimate),* Vol I (US Department of Energy, Washington, DC). Available at http://apps1.eere.energy.gov/buildings/publications/pdfs/ssl/lmc_vol1_final.pdf. Accessed October 26, 2008.

Table S2. Information sources and values for energy saved by household and transportation activities

Activity	Gallons of gasoline	Mean savings (Wh)	Reference
Setting the thermostat on your air conditioner 5 °F higher for 1 h in the summer		115	(1)
Setting the thermostat on your heater 5 °F lower for 1 h in the winter		546	(2)
Changing washer temperature settings from "hot wash, warm rinse" to "warm wash, cold rinse" for one load of laundry		4,000	(3)
Driving a more fuel efficient car (30 vs. 20 miles per gallon) at 60 miles per hour for 1 h	1	33,700	Calculated
Tuning up a car twice per year	24	808,800	(4)
Cutting highway speed from 70 miles per hour to 60 miles per hour, while driving a 20-miles-per-gallon car for 60 miles	0.4	13,480	(4)

One gallon of gasoline is equivalent to 33.7 kWh (5).

1. Armstrong M (2009) Thermostat Setbacks—Do They Really Work? Available at http://www.homeenergy.org/article_full.php?id=566&article_title=Thermostat_Setbacks%E2%80%94Do_They_Really_Work. Accessed March 7, 2009.
2. Northeast Utilities (2009) Top Ten Energy-Saving Tips. Available at: http://www.psnh.com/Residential/StartSaving/tips.asp. Accessed March 7, 2009.
3. Rocky Mountain Institute (2009) Home Energy Brief: Cleaning Appliances. Available at: http://www.rmi.org/images/PDFs/HEBs/E04-16_HEB6_CleanApps.pdf. Accessed March 7, 2009.
4. DOE (2009) A Consumer's Guide to Energy Efficiency and Renewable Energy. Available at: http://apps1.eere.energy.gov/consumer/your_home/appliances/index.cfm/mytopic=10040. Accessed March 7, 2009.
5. EPA (2009) Emission Facts: Greenhouse Gas Emissions from a Typical Passenger Vehicle. Available at: http://www.epa.gov/OMS/climate/420f05004.htm. Accessed March 7, 2009.

Table S5. Descriptive statistics for predicted elevations and slopes from model 2

	Household activities (Fig. 1; main text)		Automobiles (Fig. 2*A*; main text)		Transporting goods (Fig. 2*B*; main text) (slope)	Beverage containers (Fig. 2*C*; main text) (slope)
	Elevation	Slope	Elevation	Slope		
Perfect accuracy	0	1	0	1	1.33	1.61
Mean	−0.44	0.28	−0.01	0.24	0.54	0.40
SD	0.41	0.18	0.44	0.31	0.28	0.34
Maximum	1.01	1.08	1.90	2.51	1.15	1.18
Q3	−0.18	0.40	0.22	0.36	0.73	0.63
Median	−0.43	0.27	−0.04	0.15	0.59	0.46
Q1	−0.66	0.17	−0.31	0.06	0.37	0.19
Minimum	−2.20	−0.33	−1.45	−0.27	−0.48	−0.96

All results are from models for the 460 participants with complete data for the individual-difference variables. For transporting goods

All results are from models for the 460 participants with complete data for the individual-difference variables. For transporting goods and for beverage containers, the slopes for perfect accuracy were derived by regressing the correct ranks onto actual energy use.

Table S6. Proportions of variation explained in multilevel regressions for predicting individuals' perceptions of energy use and savings

	Model comparison	Household activities (Fig. 1; main text)	Automobiles (Fig. 2*A*; main text)	Transporting goods (Fig. 2*B*; main text)	Beverage containers (Fig. 2*C*; main text)
Variance component					
Level-1 residual, σ^2	1 vs. 0	0.40	0.58	0.23	0.09
Intercept, τ_{00}	2 vs. 1	0.11	0.01	—	—
Slope for log10*Actual*, τ_{11}	2 vs. 1	0.20	0.06	0.23	0.47
R^2					
Level 1	2 vs. 0	0.22	0.09	0.17	0.06
Level 2	2 vs. 0	0.11	0.01	0.17	0.06

In each analysis, model 0 is the null model with no predictors. Models 1 and 2 are given by Eqs. S1–S6. All calculations are based on models for the 460 participants with complete data.

https://www.pnas.org/action/downloadSupplement?doi=10.1073%2Fpnas.1001509107&file=sapp.pdf

A Survey on Energy

1. Energy-Saving Behaviors

In your opinion, what is the most effective thing that you could do to conserve energy in your life?

____

2. Energy Consumed by the Average Household

Think about an average household in the United States.

Now think about the total amount of energy that is used directly by that household in one year.

Consider that the energy used by a household can be divided into household operations, transportation and food production.

Household operations include electricity, natural gas, and heating oil that is used for the house.

Transportation includes air travel, motor travel, and public transportation used by people in the household.

Food production includes growing and shipping food that people in the household eat.

Please enter whole numbers with no other text (not decimals, ranges, or percent signs).
What percentage of the total energy consumed per year by an average household in the United States is attributed to energy used by household operations?___

What percentage of the total energy consumed per year by an average household in the United States is attributed to energy used by transportation?___

What percentage of the total energy consumed per year by an average household in the United States is attributed to energy used by food production?___

3. Energy Used by Devices in One Hour

A 100-Watt incandescent light bulb uses 100 units of energy in one hour.

How many units of energy do you think each of the following devices typically uses in one hour?

Enter a number less than 100 if you think the device uses less energy than a 100-Watt bulb. Enter a number greater than 100 if you think the device uses more energy than a

6. Energy Used to Transport Goods

In your opinion, which of the following modes of transportation uses the most energy per mile to transport one ton of goods? Please check the mode that uses the most energy, the second most, the third most, and the least energy.

	Most energy	Second most energy	Third most energy	Least energy
Ship				
Train				
Airplane				
Truck				

7. Energy Used in Recycling and Manufacturing
In your opinion, which of the following uses the most energy?

Please check the activity that uses the most energy, the second most, the third most, and the least energy.

	Most energy	**Second most energy**	**Third most energy**	**Least energy**
Making a can out of virgin aluminum				
Making a can out of recycled aluminum				
Making a glass bottle out of virgin glass				
Making a glass bottle out of recycled glass				

8. Ease or Difficulty of Energy-Saving Behaviors
Please indicate how easy or hard it would be for you to make each of the following changes.

Please consider all aspects of the changes, including the physical or mental effort required, the time or hassle involved, and any relevant monetary costs.

If you already engage in the activity please check the option on the far left.

	Do it already	Extremely easy	Very easy	Somewhat easy	Neither easy nor hard	Somewhat hard	Very hard	Extremely hard
Buying a more fuel efficient automobile (31 vs. 20 miles per gallon)	O	O	O	O	O	O	O	O
Carpooling with one other person to work	O	O	O	O	O	O	O	O
Replacing poorly insulated windows with highly insulated windows	O	O	O	O	O	O	O	O
Cutting highway speed from 70 miles per hour to 60 miles per hour	O	O	O	O	O	O	O	O
Installing a more efficient heating unit (92% efficient)	O	O	O	O	O	O	O	O
In the winter: turning down the thermostat from 72° F to 68° F during the day and to 65° F during the night	O	O	O	O	O	O	O	O
In the summer: turning up the thermostat on your air conditioner from 73° F to 78° F	O	O	O	O	O	O	O	O

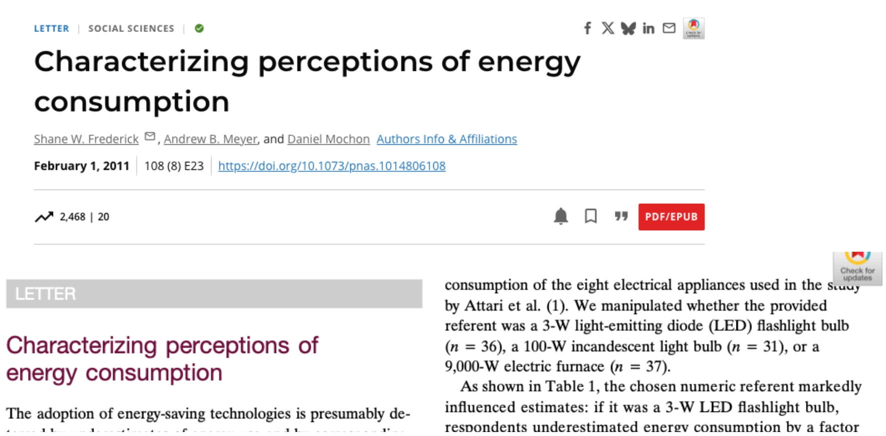
9. Ease or Difficulty of Energy-Saving Behaviors
Please indicate how easy or hard it would be for you to make each of the following changes.

Please consider all aspects of the changes, including the physical or mental effort required, the time or hassle involved, and any relevant monetary costs.

If you already engage in the activity please check the option on the far left.

	Do it already	Extremely easy	Very easy	Somewhat easy	Neither easy nor hard	Somewhat hard	Very hard	Extremely hard
Tuning up the car twice a year (including air filter changes)	O	O	O	O	O	O	O	O
Replacing 85% of all incandescent bulbs with equally bright compact fluorescent bulbs	O	O	O	O	O	O	O	O
Turning up the refrigerator thermostat from 33° F to 38° F and the freezer thermostat from –5° F to 0° F	O	O	O	O	O	O	O	O
Drying clothes on a clothes line (not using the dryer) for 5 months of the year	O	O	O	O	O	O	O	O
Watching 25% fewer hours of TV each day	O	O	O	O	O	O	O	O
Installing a more efficient washer (replace a 2001 or older non–Energy Star washer with a new Energy Star	O	O	O	O	O	O	O	O

Frederick, S. W., Meyer, A. B., & Mochon, D. (2011). Characterizing perceptions of energy consumption. *Proceedings of the National Academy of Sciences*, *108*(8), E23–E23. https://doi.org/10.1073/pnas.1014806108
https://www.pnas.org/doi/10.1073/pnas.1014806108


LETTER | SOCIAL SCIENCES |

Characterizing perceptions of energy consumption

Shane W. Frederick, Andrew B. Meyer, and Daniel Mochon Authors Info & Affiliations

February 1, 2011 | 108 (8) E23 | https://doi.org/10.1073/pnas.1014806108

2,468 | 20

PDF/EPUB

LETTER

Characterizing perceptions of energy consumption

The adoption of energy-saving technologies is presumably de-

consumption of the eight electrical appliances used in the study by Attari et al. (1). We manipulated whether the provided referent was a 3-W light-emitting diode (LED) flashlight bulb (n = 36), a 100-W incandescent light bulb (n = 31), or a 9,000-W electric furnace (n = 37).

As shown in Table 1, the chosen numeric referent markedly influenced estimates: if it was a 3-W LED flashlight bulb, respondents underestimated energy consumption by a factor terred by underestimates of energy use and by corresponding underestimates of the difference between more- and less-efficient appliances. Thus, it is easy to grasp the potential policy significance of a recent study (1) concluding that Americans underestimate energy use by a factor of 2.8.

However, the apparent precision of that statistic belies its arbitrary origins. By manipulating just two experimental details (the provided numeric referent and the units in which judgments were rendered), we show that one can readily reach qualitatively different conclusions.

For the study in question (1), respondents were first told that a 100-W incandescent electric light bulb uses 100 units of energy in 1 h and were then asked to estimate the energy use of various household appliances. The experimental decision to provide a 100-W light bulb as the referent was justified by respondents' familiarity with light bulbs and by the authors' corresponding conjecture that a light bulb might serve as a natural reference point for such judgments, even if not explicitly provided as part of the experimental materials.

Using an online panel of survey participants, we first tested whether a light bulb would serve as a natural reference point for judgments about energy use. Of 100 participants asked to name something that uses energy to operate, a total of 12 mentioned light, lights, or a light bulb. Other responses included computer (30), car (13), television (11), air conditioner (4), coffee pot (2), toaster (2), vacuum (2), and chain saw (2).

We then tested for the influence of the provided numeric referent. A separate set of respondents estimated the energy

of 18.3; if it was a 100-W incandescent light bulb, they underestimated consumption by a factor of 2.5 (strikingly close to the value reported by Attari et al.); and if it was a 9,000-W electric furnace, they *overestimated* consumption by a factor of 1.6. In two other conditions ($n = 38$ and $n = 39$), we provided no referent but manipulated the units in which judgments were rendered. When responding in watts, respondents underestimated energy use by a factor of 6, but when responding in kilowatts, they *overestimated* energy use by a factor of 51. In our view, such results call into question the validity of the summary statistics proposed in the target article (1).

ACKNOWLEDGMENTS. We thank Edward Hall, Daniel Read, and colleagues at Yale for comments.

Shane W. Frederick[a,1]***, Andrew B. Meyer***[a]***, and Daniel Mochon***[b]
[a]*Marketing Department, Yale School of Management, New Haven, CT 06511; and* [b]*Marketing Department, Rady School of Management, University of California at San Diego, La Jolla, CA 92093*

1. Attari SZ, DeKay ML, Davidson CI, Bruine de Bruin W (2010) Public perceptions of energy consumption and savings. *Proc Natl Acad Sci USA* 107:16054–16059.

Author contributions: S.W.F., A.B.M., and D.M. designed research; S.W.F., A.B.M., and D.M. performed research; S.W.F. and A.B.M. analyzed data; and S.W.F., A.B.M., and D. M. wrote the paper.

The authors declare no conflict of interest.

[1]To whom correspondence should be addressed. E-mail: shane.frederick@yale.edu.

Table 1. Median judgments (watts)

Provided referent	Laptop computer (48)	Stereo (128)	Desktop (140)	Heater (925)	Room AC (1,000)	Dishwasher (1,800)	Dryer (3,400)	Central AC (3,500)	Average (1,368)
3-W LED flashlight bulb	25	23	33	73	78	73	100	150	75
100-W light bulb	200	125	340	500	500	300	500	800	544
9,000-W electric furnace	350	300	500	1,000	2,000	1,200	1,000	6,000	2,188

Actual energy consumption, as reported by Attari et al. (1), in parentheses. AC, air conditioner.

Frederick reports actual empirical estimate medians
https://pmc.ncbi.nlm.nih.gov/articles/PMC3044394/

18.3; if it was a 100-W incandescent light bulb, they underestimated consumption by a factor of 2.5 (strikingly close to the value reported by Attari et al.); and if it was a 9,000-W electric furnace, they *overestimated* consumption by a factor of 1.6. In two other conditions ($n = 38$ and $n = 39$), we provided no referent but manipulated the units in which judgments were rendered. When responding in watts, respondents underestimated energy use by a factor of 6, but when responding in kilowatts, they *overestimated* energy use by a factor of 51. In our view, such results call into question the validity of the summary statistics proposed in the target article (1).

Table 1.

Median judgments (watts)

Provided referent	Laptop computer (48)	Stereo (128)	Desktop (140)	Heater (925)	Room AC (1,000)	Dishwasher (1,800)	Dryer (3,400)	Central AC (3,500)	Average (1,368)
3-W LED flashlight bulb	25	23	33	73	78	73	100	150	75
100-W light bulb	200	125	340	500	500	300	500	800	544
9,000-W electric furnace	350	300	500	1,000	2,000	1,200	1,000	6,000	2,188

Open in a new tab

Actual energy consumption, as reported by Attari et al. (1), in parentheses. AC, air conditioner.

https://www.pnas.org/doi/pdf/10.1073/pnas.1019040108

were presumably difficult. The kilowatt condition seems

Reply to Frederick et al.: Anchoring effects on energy perceptions

Both our study (1) and the follow-up described by Frederick et al. (2) indicate that people know relatively little about how much energy is used by different devices and appliances. In our view, the additional data strengthen rather than weaken our original conclusions.

It is well known that numerical judgments are subject to anchoring effects, with initial values having substantial influence on final answers (3). In our article, we noted that the compressed range of respondents' energy estimates "almost certainly resulted from an anchoring bias in which the reference point provided in the task served as an anchor for participants' estimates, causing those estimates to be too similar to the reference point" (p 16057). This compression, combined with a relatively low reference point (a 100-W light bulb used for 1 h), contributed to the underestimation of energy use. We also predicted that "it would be possible to eliminate this underestimation (or even generate overestimation) by using a higher reference point" (*SI Text*, p 2). The follow-up study replicates our results for the light-bulb reference point and confirms the expected effects of other reference points on means and ranges, thereby verifying our account.

Before implementing our survey, we conducted several interviews in which participants thought out loud while estimating the energy use of different appliances, as commonly suggested in the survey-design literature (4). Without a reference point, interviewees found it hard to judge the energy use of different devices; however, using a light bulb as a reference (as opposed to other devices) made the quantitative judgments easier.

Frederick et al. (2) report that the most common response to the prompt "name something that uses energy to operate" was "computer" (30%). Although these participants were not necessarily selecting a reference point for energy estimates, the average 1-h energy use of a laptop and desktop computer [about (48 + 140)/2 = 94 Wh] is remarkably close to our light-bulb reference point (100 Wh). Any reference point in this range would lead to similar estimation results.

Because many people do not know what constitutes a watt or kilowatt, Frederick et al.'s two no-reference-point conditions were presumably difficult. The kilowatt condition seems particularly hard: because half the devices listed are rated as less than 1 kW, correct responses would have to be typed as decimals. Thus, we are not surprised that the 51-fold overestimation with kilowatts was larger than the sixfold underestimation with watts. More telling is that the average numerical responses in the two conditions differed by a factor of only $(1{,}368/6)/(1.368 \times 51) = 3.3$ rather than 1,000. Therefore, what looks like a huge difference is actually *insensitivity* to the change of units.

In summary, we agree with Frederick et al. that estimates of energy use are labile. This instability follows from the lack of available information and people's lack of knowledge about energy use. However, when people choose their own (typically low) reference points, they underestimate the energy use of home appliances and underestimate the range of energy use among appliances. Correcting such misperceptions may be a necessary precursor to narrowing the US energy efficiency gap (5).

ACKNOWLEDGMENTS. This work was supported by the Francois Fiessinger Scholarship (to S.Z.A.), National Science Foundation Grants DUE-0442618 and SES-0345840, Center for Research on Environmental Decisions, and the Earth Institute.

Shahzeen Z. Attari[a,1]***, Michael L. DeKay***[b]***, Cliff I. Davidson***[c]***, and Wändi Bruine de Bruin***[d]

[a]*The Earth Institute and Center for Research on Environmental Decisions, Columbia University, New York, NY 10027;* [b]*Department of Psychology, Ohio State University, Columbus, OH 43210;* [c]*Syracuse Center of Excellence in Environmental and Energy Systems and Department of Civil and Environmental Engineering, Syracuse University, Syracuse, NY 13244; and* [d]*Departments of Engineering and Public Policy and Social and Decision Sciences, Carnegie Mellon University, Pittsburgh, PA 15213*

1. Attari SZ, DeKay ML, Davidson CI, Bruine de Bruin W (2010) Public perceptions of energy consumption and savings. *Proc Natl Acad Sci USA* 107:16054–16059.
2. Frederick SW, Meyer AM, Mochon D (2011) Characterizing perceptions of energy consumption. *Proc Natl Acad Sci USA* 108:E23.
3. Tversky A, Kahneman D (1974) Judgment under uncertainty: Heuristics and biases. *Science* 185:1124–1131.
4. Converse J, Presser S (1986) *Survey Questions: Handcrafting the Standardized Questionnaire* (Sage Publications, Thousand Oaks, CA).
5. Dietz T (2010) Narrowing the US energy efficiency gap. *Proc Natl Acad Sci USA* 107: 16007–16008.

Author contributions: S.Z.A., M.L.D., C.I.D., and W.B.d.B. wrote the paper.

The authors declare no conflict of interest.

[1]To whom correspondence should be addressed: E-mail: shahzeen.attari@gmail.com.

Marghetis, T., Attari, S. Z., & Landy, D. (2019). Simple interventions can correct misperceptions of home energy use. *Nature Energy*, *4*(10), 874–881. https://doi.org/10.1038/s41560-019-0467-2

Simple interventions can correct misperceptions of home energy use

Second, to generate numerical estimates, individuals must transform their underlying understanding of appliances' energy use into explicit responses on some external response scale (for example, watt-hours). Misusing this scale may produce massive over- or underestimates, even if the underlying understanding is accurate. This is true not only for energy but for numerical estimation in general[16]. Across a variety of domains (for example, space[17], risk[18], demographic proportions[19]), the transformation from internal information to external response scale has been found to introduce distortions into estimates[20]. For instance, when presented with a display of black and white dots, people systematically overestimate the proportion of black dots when there are few, and underestimate the proportion when there are many[21], not because they are incapable of perceiving the dots, but because of how they translate their internal perceptions into explicit proportions. In the case of energy use, even if people had a perfect understanding of appliances' energy use, they may fail to make accurate estimates if they were unfamiliar with the measurement units. For example, people may understand that charging a smartphone uses little energy and that an oven uses much more, but they may fail to translate those beliefs into reasonable values on the watt-hour scale. Indeed, previous work has found that people systematically overestimate the energy used by low-use appliances, but underestimate the energy used by high-use appliances[3,4,22]. Misestimations at both ends of the scale are of practical concern because both can lead to suboptimal decisions. Moreover, this pattern, which resembles the case of dot estimation described above, suggests a possible source for these errors: a general failure to use the response scale correctly.

These two factors (underlying understanding and use of the response scale) differ in their potential repercussions. Distortions in underlying understanding have repercussions both for explicit quantitative estimations of home energy use and for energy-related behaviour. On the other hand, misusing the response scale (for example, watt-hours) may introduce systematic distortions into estimates, without necessarily distorting energy-related behavioural decisions, because decisions may reflect underlying beliefs rather than numerical reports of those beliefs. Indeed, in other domains, numerical 'anchoring' interventions that have large impacts on numerical judgements seldom have downstream effects on behaviour[23]. Thus, our account predicts that some interventions that improve energy estimates will have little effect on energy-related behaviours. For instance, if an intervention only improved the use of the response scale, it might have large effects on energy estimation without necessarily benefitting energy-related behaviours. Conversely, if an intervention improved underlying understanding, it might have minimal benefits for

This account informed the development of two interventions for improving home energy estimation. First, we targeted the use of the response scale by supplying quantitative information about the extremes of electricity use (the typical energy use in 1 h by phone chargers, 5 Wh, and clothes dryers, 4,000 Wh). We predicted that this 'scale-use' intervention would help participants translate their beliefs about energy use into explicit estimates on the watt-hours scale without necessarily improving either their beliefs or their decisions that were based on those beliefs. Second, we targeted systematic misunderstandings by supplying a simple 'explicit heuristic' or guiding rule[24]. People underestimate the energy used by appliances that change the temperature[3], perhaps because heat generation and heat removal may not be as noticeable as movement or lighting. This observation inspired the following explicit heuristic: large appliances that primarily heat or cool use a lot more energy than people think they use. Unlike the scale-use intervention, this explicit heuristic was intended to correct the underlying beliefs rather than just the way those beliefs are expressed in watt-hours. Therefore, in addition to improving explicit estimates of energy use, we predicted that teaching this heuristic to individuals might improve their behavioural choices by helping them identify and potentially adopt effective conservation strategies.

Estimates of home energy use

In an online experiment ($N = 1{,}645$), we investigated how these interventions affected the ability to estimate the electricity used by home appliances and whether they improved the ability to choose between energy-conserving actions. Participants received neither, one, or both of the interventions (scale use and explicit heuristic). We also investigated how the misperception of home energy use related to pro-environmental behaviours, attitudes, climate change beliefs and support for climate policy.

We first measured participants' ability to estimate home energy use. Participants estimated the electricity used in 1 h by 36 home appliances (for example, clock, desktop computer, electric oven). In the control condition, in which participants did not receive either of the interventions, estimates were off by nearly an order of magnitude (mean absolute relative error: $M = 7.0$, 95% confidence interval (CI) [3.6, 10.4]). This aggregate error, however, hid a systematic pattern that has been described previously: energy use by appliances that use less energy was overestimated, whereas energy use by those that use more energy was underestimated[3,4,22,25] (Fig. 1). Therefore, following past work[3,25], we focussed on the systematic relation between appliances' actual energy use and participants' estimates of those values. This relation is illustrated in Fig. 1a,b by the slope of the relation between actual

Attari, S. Z. (2014). Perceptions of water use. *Proceedings of the National Academy of Sciences*, *111*(14), 5129–5134.
https://doi.org/10.1073/pnas.1316402111
https://www.szattari.com/publications

Table 1. Categorized responses to the two open-ended questions about the single most effective thing participants could do to conserve water in their lives, and the single most effective thing Americans could do to conserve water in their lives

Activity	Curtailment (C) or efficiency (E)	Self, %	Americans, %
Shorter or fewer showers	C	42.6	28.0
Turn off water while doing other activities (not including brushing teeth)	C	9.9	10.0
Turn off water while brushing teeth	C	6.9	6.7
Conserve water or use water efficiently	—	4.5	6.6
Do less laundry or full loads of laundry	C	4.3	2.2
Pay more attention to water use	—	4.2	6.4
Water lawn less	C	4.1	12.5
Reduce dishwasher use or hand wash dishes	C	3.6	1.0

Other reason (mentioned once)	—	3.2	3.6
Harvest water by using rain barrels	E	2.4	1.6
Check for leaks and repair them	—	2.1	2.9
Bathe less and shower instead	E	1.8	1.5
Switch to water-efficient fixtures/technologies	E	1.7	2.4
Water-efficient toilet	E	1.5	2.4
Flush less	C	1.2	1.4
Turn off shower while shampooing and soaping	C	1.0	1.3
Switch to low-flow showerheads	E	0.9	1.1
Eat less meat	C	0.8	1.0
Switch to low-flow faucets	E	0.7	1.1
Don't drink bottled water	C	0.6	1.9
Recycle	—	0.5	0.7
Wash car less	C	0.5	1.2
Get rid of lawns or switch to water-efficient plants	E	0.5	2.2
Switch to water-efficient clothes washing machines	E	0.4	0.4
Buy fewer products	C	0.3	0.4

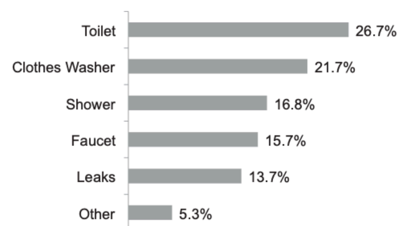


Fig. 1. Disaggregated residential indoor water use based on 12 study sites in the United States published in 1999, adapted from Mayer et al. (5).

greatest savings (71%) in indoor household water use (14), followed by retrofitting clothes washers (19%), showerheads (5%), and faucet aerators (5%). (Even though toilets use less water volumetrically than washers and showers per use, the frequency of use results in higher water use overall.) Note that a more subtle classification of the categories would be to code them as "intent-oriented" or "impact-oriented" behaviors (15). In intent-oriented behaviors, the intention to help the environment shapes the behavior without taking the actual environmental impact or effectiveness into account, such as turning off the water while brushing teeth. Alternatively, impact-oriented behaviors are focused on making a large difference, such as retrofitting toilets. The gap between intent- and impact-oriented actions may be explained by the lack of information (people do not know what is effective) or the lack of motivation (people are not motivated to act out effective behaviors). However, further research is needed to clearly classify the elicited behaviors in this manner.

Table 1 shows a major shift between endorsing fewer/shorter showers for oneself vs. endorsing watering the lawn less for others. Even though both these activities are classified as curtailment (restrictions on consumption), the shift could indicate that participants know that watering the lawn less is an effective action.

Fig. 2 shows the relative joint percentage distribution of responses for self and for other Americans using three categories: curtailment, efficiency, and other. Fig. 2 also displays a significant asymmetry as highlighted by the arrow, indicating that participants are more likely to recommend curtailment actions for themselves and efficiency actions for others than vice versa [$\log(7.6/4.0) = 0.64 \pm 0.26$, $P \approx 0.001$]. One reason for this asymmetry may be the upfront capital costs involved with efficiency actions (i.e., "I cannot afford the retrofits, but perhaps others can"). Further investigation to tease out why this asymmetry exists will be needed to more fully understand the self/other bias.

To explore order effects, Fig. 2 can be divided into two 3×3 tables (self/American vs. American/self), with the three categories (see Fig. S1 in *SI Text*). Note that the two tables are fairly similar and the hypothesis of identical joint distributions cannot quite be rejected: $\chi^2 = 13.63$ (likelihood-ratio test, 8 df). Given the absence of appreciable order effects, the data from the two orders of presentation are combined here and later.

Perceptions of Water Use. Before conducting the current study, a survey designed to elicit preferred units of measuring water quantity was conducted. Specifically, participants from a university community were asked the following question:

> Water quantity can be measured in several possible units: milliliters, customary (US) ounces, cups, quarts, liters, gallons, cubic feet, cubic meters, tons, etc. When thinking about water use, what units of measurement are you most comfortable with?

Of the 225 participants who completed this open-ended question, 73.3% stated gallons, 16.9% stated liters, 5.8% stated

level) were not reliable predictors in these regressions.

The mean judged ranks for embodied water use scarcely vary among the four goods, as shown in Fig. 5. No combination of the 10 centered individual difference variables correlate appreciably with this slope [$r^2 = 0.017$, $F(10, 974) = 1.75$].

Discussion

When asked what is the most effective action they can take to decrease their water use, participants stated curtailment actions rather than efficiency actions, possibly because of the upfront monetary costs involved with efficiency actions. Results also show a significant asymmetry indicating that some participants are more likely to recommend curtailment actions for themselves and efficiency actions for others than vice versa.

As shown in Fig. 1, toilets use the most volume of water indoors and their suggested retrofits is the top recommendation made by the EPA (14). However, "buying water-efficient appliances and fixtures" along with "water-efficient toilet" and "flushing less" are among the least-mentioned actions as shown in Table 1. One reason why participants did not mention toilets or flushes may be due to ignoring the frequent but short duration daily exposures related to these behaviors in contrast to single but longer daily exposure related to showers, which topped the list.

Participants in this study did have some knowledge about water used by a variety of activities, as illustrated by the slope of the curve in Figs. 3 and 4, which is somewhat close to the diagonal line. The observed correlation between judged and actual water use is positive and large. However, as water use increases, participants tend to compress the actions together, underestimating the relative differences between different actions that use a lot of water. Older participants were more accurate, indicating that the experience that comes along with age may be leading to more accurate perceptions of water use. Being male and numerate also led to more accurate perceptions. Although pro-environmental attitudes were shown to be important predictors of accuracy for energy consumption (9), they do not seem to be as important for accurate judgments of water use.

Another challenge highlighted by this study is that participants systematically underestimate the water used by standard appliances and fixtures, however they tend to overestimate some efficient appliances (efficient dishwashers and flushes) while underestimating others. Given standard appliances and fixtures are

20). Note that anchoring effects play no role in Fig. 5, because a referent was not provided in the ranking task.

In contrast to perceptions of energy consumption (9) which were not very encouraging, participants here had more accurate perceptions of water use and tended to underestimate water use less compared with results from the energy study (Fig. 4). One reason why perceptions of water use are more accurate may be due to the consistent physical characteristics of water as opposed to energy, which is transformed based on the end-use activity (e.g., heating, cooling, lighting, motion). Another reason for greater accuracy for water use is that most Americans make decisions about gallons of liquid nearly every day (e.g., buying gasoline or milk), therefore the unit of measurement may be much more familiar for water use than for energy use. Even though perceptions of water use are more accurate, there is still significant underestimation over the range of activities explored in this study. One reason for this underestimation is due to anchoring and insufficient adjustment (12). However, using gallons as a unit of measure may be a natural anchor that Americans use to think about water volumes in the United States. Of course using larger units of measure would lead to overestimation (21, 22), but based on the presurvey results, gallons was used as a unit of measure in the survey as it may be the preferred natural unit for these judgments. Thus, the observed underestimation should generalize beyond this survey.

This study, like that of Attari et al. (9), has many limitations. Monetary incentives were not offered for accuracy and an Internet sample was used, which was not completely representative of the US population. The actual water-use data have limitations due to availability of data, as they come from a variety of sources and snapshots in time, which is a documented problem in this field (23). It is important to note that the data in Fig. 1 is about 14 y old, even though it is the best available data and is currently being used by the EPA (4). It may be the case that with new regulations and technology, the distribution of water use in the home (as shown in Fig. 1) has shifted over time.

Price signals related to residential water use were a factor omitted from the study that could serve as an important predictor for accuracy. However, pay structures for residential water use vary widely in the United States (e.g., uniform cost per month independent of consumption, uniform rates, progressive or increasing block rates, and regressive or decreasing block rates) (24, 25). Gaudin (25) found that in a sample of 383 water utilities in the United States, only 17% of the utilities indicated

Schley, D. R., & DeKay, M. L. (2015). Cognitive accessibility in judgments of household energy consumption. *Journal of Environmental Psychology*, *43*, 30–41. https://doi.org/10.1016/j.jenvp.2015.05.004

Table A.1

End-use categories and percentages of national (U.S.) annual individual and household energy consumption

End-use categories and percentages of national (U.S.) annual individual and household energy consumption.

End-use category	Study 1[a]	Studies 2 and 4[a]	Study 3[b]
Dishwashers	0.4	0.2	0.8
Swimming pool heaters, grills, and outdoor gas lamps[c]	0.9	0.5	In "Other"
Computers[d]	1.1	0.6	1.6
Mass transportation (personal travel on buses, trains, and ships)	–	1.4	–
Cooking	2.7	1.5	3.2
Televisions[e]	4.4	2.5	2.4
Clothes washing and drying	4.4	2.5	3.1
Air travel	–	3.4	–
Small electric appliances	6.9	3.9	In "Other"
Refrigeration and freezing	7.6	4.3	4.0
Lighting	10.8	6.1	6.4
Air conditioning	11.0	6.2	7.5
Water heating (including hot water for clothes washing)[f]	11.5	6.5	17.5
Home heating[g]	33.2	18.8	44.2
Private motor vehicles	–	38.6	–
Other individual and household energy use[h]	5.3	3.0	9.3

[a] Percentages are from Gardner and Stern's (2008) Table 1, rescaled to sum to 100% (within rounding) in Study 1.
[b] Percentages are based on the "delivered energy consumption by end use" section of the USEIA's (2012) Table A4.
[c] In Study 1: Swimming pool heaters, grills, and outdoor heating lamps.
[d] In Study 3: Personal computers and related equipment.
[e] In Study 3: Color televisions and set-top boxes.
[f] In Study 1: Water heating; in Study 3: Water heating (including hot water for clothes and dish washing).
[g] In Study 1 (student participants): Space heating; in Study 3: Home heating (including furnace fans and boiler circulation pumps).
[h] In Study 1: Other; in Study 3: Other devices (small electric devices, heating elements, motors, outdoor grills, etc.).

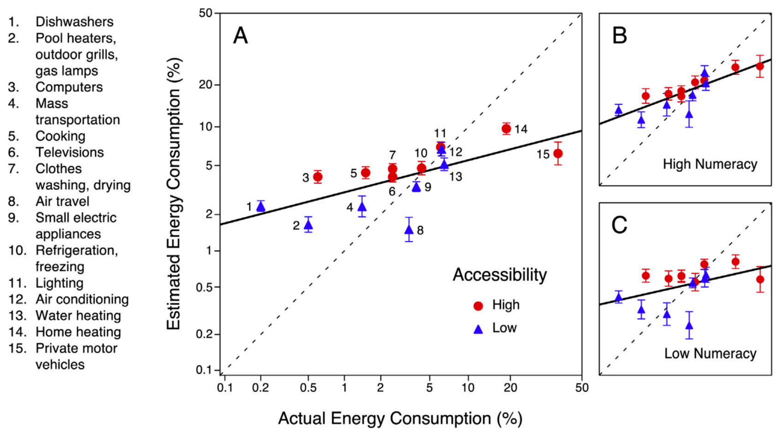


Fig. 1. Mean estimated energy consumption as a function of actual consumption for 15 end-use categories, with 95% confidence intervals, for (A) all Study 2 participants, (B) high-numeracy participants (top quartile), and (C) low-numeracy participants (bottom quartile). We show Study 2 data because that study used the greatest number of categories. Accessibility is dichotomized for illustration only. See the Appendix for category details.

The materials for all four surveys are presented below. These were computer surveys, so the materials here do not look exactly like they did in the actual experiments.

STUDY 1

Welcome to the Household Energy Survey. Please answer the questions to the best of your ability, without looking up any answers online. Please press the ">>" button to begin the survey.

Please consider the total amount of energy (electricity, natural gas, propane, or heating oil) used by typical American households in a given year. Please indicate what percentage of total energy you think is used by devices or appliances in that category for typical American households. Each time you type a number into a box, the bottom box "Total" will adjust to let you know how many percentage points you have used. You can change any of your answers until you are satisfied. You are not expected to know the exact answers, but give your best estimate. After you have assigned all 100 percentage points, and you are content with your answers, please press the ">>" button.

______ SMALL ELECTRIC APPLIANCES
______ TELEVISIONS
______ SPACE HEATING
______ LIGHTING
______ CLOTHES WASHING/DRYING
______ DISHWASHERS
______ COOKING
______ WATER HEATING
______ AIR CONDITIONING
______ SWIMMING POOL HEATERS, GRILLS, AND OUTDOOR HEATING LAMPS
______ REFRIGERATORS/FREEZERS
______ COMPUTERS
______ OTHER

For each of the following categories, please indicate how often you INTERACT WITH items in that category. By "INTERACT WITH," we mean turning the device on, turning the device off, or adjusting the device in some way.

	Never	Rarely	Occasionally	Moderately Often	Very Often

SMALL ELECTRIC APPLIANCES	❍	❍	❍	❍	❍
TELEVISIONS	❍	❍	❍	❍	❍
SPACE HEATING	❍	❍	❍	❍	❍
LIGHTING	❍	❍	❍	❍	❍
CLOTHES WASHING/DRYING	❍	❍	❍	❍	❍
DISHWASHERS	❍	❍	❍	❍	❍
COOKING	❍	❍	❍	❍	❍
WATER HEATING	❍	❍	❍	❍	❍
AIR CONDITIONING	❍	❍	❍	❍	❍
SWIMMING POOL HEATERS, GRILLS, AND OUTDOOR HEATING LAMPS	❍	❍	❍	❍	❍
REFRIGERATORS/FREEZERS	❍	❍	❍	❍	❍
COMPUTERS	❍	❍	❍	❍	❍
OTHER	❍	❍	❍	❍	❍

Starke, A. D., Willemsen, M. C., & Snijders, C. C. P. (2020). Beyond "one-size-fits-all" platforms: Applying Campbell's paradigm to test personalized energy advice in the Netherlands. *Energy Research & Social Science*, *59*, 101311.
https://doi.org/10.1016/j.erss.2019.101311

Energy Research & Social Science

journal homepage: www.elsevier.com/locate/erss

Original research article

Beyond "one-size-fits-all" platforms: Applying Campbell's paradigm to test personalized energy advice in the Netherlands

Alain D. Starke*, Martijn C. Willemsen, Chris C.P. Snijders

Human-Technology Interaction Group, Eindhoven University of Technology, PO 513, 5600MB Eindhoven, the Netherlands

ARTICLE INFO

Keywords:
Conservation advice
Energy efficiency
Rasch model
Recommender systems

ABSTRACT

When analyzing ways in which people save energy, most researchers and policy makers conceptually differentiate between curtailment (e.g. unplugging chargers) and efficiency measures (e.g. installing PV cells). However, such a two-dimensional approach is suboptimal from both a conceptual and policy perspective, as it does not consider individual differences that determine energy-saving behavior. We propose a different, one-dimensional approach, applying Campbell's Paradigm through the Rasch model, in which both curtailment and efficiency measures are intermixed on a single scale and ordered according to their behavioral costs. By matching these behavioral costs to individual energy-saving attitudes, we investigate to what extent attitude-tailored energy-saving advice can help consumers to save energy.

We present the results of two studies. The first study ($N = 263$) reliably calibrated a one-dimensional Rasch scale that consists of 79 energy-saving measures, suitable for advice. The second study employed this scale to investigate how users ($N = 196$) evaluate attitude-tailored energy-saving advice in a web-based energy recommender system. Results indicate that Rasch-based recommendations can be used to effectively tailor energy-saving advice and that such attitude-tailored advice is more adequate than a number of non-personalized approaches.

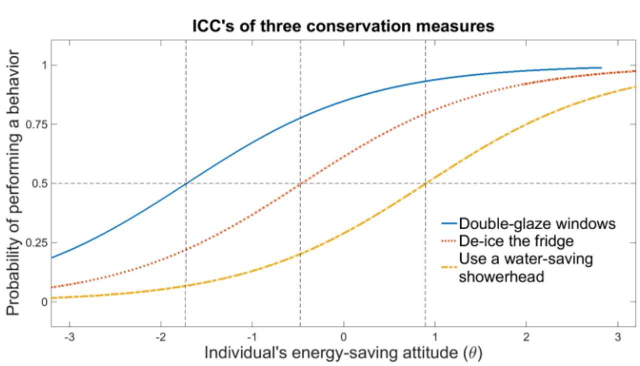


Fig. 1. Item-characteristic curves (ICC's) of three conservation measures with different behavioral cost levels, yielding varying engagement probabilities as a function of an individual's energy-saving attitude.

efficiency measure as the use of green energy had a lower behavioral cost level than turning off the lights after leaving a room, a curtailment measure.

information filtering systems that rely on a user's input, such as ratings or self-reported behavior, and subsequently provide user-tailored recommendations by drawing upon an extensive database of domain

2.4. Attitude-tailored advice

To determine how to use the Rasch model to provide suitable attitude-tailored advice to individuals, we can draw upon several model characteristics. We have already shown that, regardless of one's energy-saving attitude, some measures bear lower behavioral costs than others and are therefore more likely to be performed. In addition, such a high probability implies that a measure's benefits outweigh its behavioral costs [22], deeming such low-cost behaviors to be more feasible than their high-cost counterparts. However, only suggesting low-cost measures to an individual would lead to rather redundant advice, as most of them would already be performed.

To account for this trade-off between feasibility and redundancy, we expect that tailoring energy-saving advice around an individual's energy-saving attitude is an effective approach. This would result in adequate advice, as a measure's perceived benefits would be roughly equal to its behavioral costs, while such measures could still be relevant or novel to an individual as they would still have about a 50% prob-

items, such as movies or online dates [43,44]. Analogously, energy recommender systems can help consumers to overcome their often limited knowledge on what actions to take to reduce their energy consumption [26,45], allowing them to discover effective energy-saving measures that fit their profile [30]. However, prior research on energy recommender systems has predominantly focused on optimizing the user experience, by matching the preference elicitation method with the domain knowledge of the user [30]. Similarly, the Rasch scale developed in the current research has already been applied in another energy recommender study that focuses on user experience aspects [46], which was published ahead of the current paper. However, the present paper discusses more in-depth the theoretical and policy implications of the Rasch model.

The current research examines the validity of a one-dimensional Rasch construct for energy-saving behavior, as well as how it can be used for attitude-tailored advice. While preceding research inferred constructs that captured at most 40 environmental behaviors [41], we design a web-based conservation tool that draws upon a database of 88 energy-saving measures [47], which we use to fit a Rasch scale that is

Table 1
Behavioral cost levels (δ) and infit indices (Mean Square (MS) and Standardized Values (ZSTD)) for two Rasch scales of energy-saving measures, for Study 1 and Study 2 (cf. Section 4.2.1). The two scales have similar behavioral cost levels: $r(79) = 0.88$. 'Set' denotes the 13 different sets from which measures are sampled for attitude calibration in Study 2.

		Study 1 Infit			Study 2 Infit			
#	Name of energy-saving measure (translated)	δ	MS	ZSTD	δ	MS	ZSTD	Set
1	Save up laundry	**−5.73**	Min	Min	**−3.23**	1.14	0.4	1
2	Take a shower instead of a bath	**−4.82**	0.95	0.2	**−4.41**	Min	Min	1
3	Wash laundry at low temperatures	**−3.95**	1.14	0.4	**−1.64**	1.01	0.1	1
4	Air-dry laundry	**−3.69**	0.99	0.1	**−2.93**	1.19	0.5	1
5	Use a laptop instead of a desktop PC	**−3.45**	1.04	0.2	**−3.62**	1.16	0.5	1
6	Turn off the lights after leaving a room	**−2.97**	0.85	−0.3	**−2.78**	0.69	−1.0	1
7	Use public transportation instead of a car	**−2.90**	1.10	0.4	**−2.52**	1.42	1.4	1
8	Use a woolen blanket instead of an electric blanket	**−2.51**	0.99	0.1	**−3.03**	1.05	0.3	2
9	Use properly sized cooking equipment	**−2.51**	0.88	−0.2	**−2.69**	0.66	−1.2	2
10	Lower the thermostat while away from home	**−2.49**	0.97	0	**−1.92**	0.79	−1.0	2
11	Do not put warm things in the fridge	**−2.45**	0.69	−1.3	**−2.40**	0.97	−0.1	2
12	Turn off the PC screen after use	**−2.20**	0.97	0	**−0.71**	1.08	0.6	2
13	Close the curtains/shutters in the evening	**−2.09**	1.07	0.4	**−1.57**	1.03	0.3	2
14	Shift gears at low speeds	**−1.89**	1.02	0.2	**−2.07**	0.81	−1.1	3
15	Cook with a lid on the pan	**−1.81**	0.91	−0.5	**−1.81**	0.93	−0.5	3
16	Use energy-saving bulbs (CFL's)	**−1.75**	0.81	−1.1	**−1.31**	0.76	−2.7	3
17	Double-glaze windows	**−1.72**	0.81	−0.9	**−1.24**	1.01	0.1	3
18	Air rooms for 20 min daily	**−1.51**	0.95	−0.3	**−1.21**	1.13	1.2	3
19	Cook on gas stove instead of electric	**−1.36**	1.34	1.7	**−2.23**	1.30	1.6	3
20	Lower the thermostat one degree	**−1.25**	1.02	0.2	**−0.47**	1.01	0.1	4
21	Set thermostat to 14 °C before going to bed	**−1.20**	0.97	−0.2	**−0.90**	1.14	1.4	4
22	Do not defrost food using a microwave	**−1.18**	1.04	0.3	**−0.52**	1.16	1.7	4
23	Turn off the TV instead of stand – by	**−1.06**	1.26	1.1	**−0.74**	0.96	−0.4	4
24	Maintain correct tire pressure	**−0.94**	0.86	−0.5	**−0.27**	1.06	0.5	4
25	Stir-fry food	**−0.91**	1.08	0.7	**−0.62**	1.01	0.1	4
26	Turn off the PC at the main switch	**−0.81**	0.90	−0.9	**−0.21**	0.99	−0.1	5
27	Turn off the coffee machine completely	**−0.57**	0.91	−0.7	**−1.30**	0.94	−0.4	5
28	Turn off the dishwasher after use	**−0.57**	0.77	−1.8	**−0.37**	0.99	−0.1	5
29	Insulate the cavity wall	**−0.51**	1.20	0.9	**0.50**	0.89	−0.9	5
30	Turn off the washing machine completely	**−0.49**	0.91	−1.0	**−0.22**	1.00	0	5
31	De-ice the fridge	**−0.46**	0.96	−0.3	**0.59**	0.98	−0.2	5
32	Unplug chargers	**−0.32**	1.01	0.1	**−0.44**	0.98	−0.2	6
33	Take short showers	**−0.29**	1.13	1.6	**0.52**	0.92	−0.8	6
34	Hand-wash dishes (no dish washer)	**−0.22**	1.33	2.7	**−0.72**	1.32	2.9	6
35	Configure PC power management	**0.00**	1.15	1.4	**0.29**	1.00	0.1	6
36	Shorten PC/laptop stand-by time	**0.01**	0.90	−0.6	**−0.43**	0.84	−1.8	6
37	Air clothes instead of washing them	**0.07**	1.06	0.7	**−0.39**	1.10	1.1	6
38	Clean the cooker hood suction filters	**0.14**	1.02	0.2	**0.29**	1.10	0.7	7
39	Place fridge in a suitable position	**0.18**	1.00	0.1	**−0.14**	0.78	−1.2	7
40	Use LED lighting	**0.37**	1.04	0.5	**0.38**	0.89	−0.8	7
41	Decalcify your coffee machine and/or kettle	**0.40**	0.96	−0.3	**0.35**	0.88	−1.1	7
42	Sweep instead of using a vacuum cleaner	**0.43**	1.21	1.6	**0.40**	1.06	0.6	7
43	Use a smart thermostat	**0.47**	1.06	0.5	**−0.11**	0.88	−1.4	7
44	Put a weather strip on the door	**0.47**	0.75	−2.5	**0.19**	0.89	−1.4	8
45	Use a HE boiler or CHP	**0.47**	0.96	−0.2	**0.98**	0.96	−0.2	8
46	Use household devices without displays	**0.48**	1.20	1.3	**2.67**	0.99	0.1	8
47	Use an 'A+' energy-class fridge	**0.51**	0.87	−1.3	**−0.09**	0.90	−1.0	8
48	Install motion sensors	**0.51**	0.81	−1.9	**−0.02**	1.06	0.5	8

Appendix B

Individual correlation coefficients for Design 4

Table B1
Correlation coefficient for each within-participant participant's estimate of perceived size and perceived energy consumption.

Participant ID	Correlation coefficient (r_s)
1	0.39
2	0.66
3	0.69
4	0.61
5	0.70
6	0.46
7	0.82
8	0.84
9	0.11
10	0.68
11	0.59
12	0.50
13	0.62
14	0.56
15	0.80
16	0.85
17	0.81
18	0.11
19	0.58
20	0.60
21	0.23
22	0.65
23	0.67
24	0.41
25	0.67
26	0.88
27	0.39

Appendix C

Individual correlation coefficients for the accuracy test with MO method

Table C1
Correlations between each participant's estimates and the actual size and energy consumption of the appliances.

Participant ID	Estimated and Actual Size		Estimated Size and Actual Energy		Estimated and Actual Energy	
	b-p	w-p	b-p	w-p	b-p	w-p
1	0.82	0.94	0.88	0.88	0.16	0.50
2	0.88	0.91	0.87	0.86	−0.15	0.82
3	0.81	0.95	0.84	0.84	0.74	0.74
4	0.91	0.84	0.81	0.80	0.59	0.57
5	0.88	0.90	0.89	0.86	0.00	0.68
6	0.45	0.89	0.61	0.86	0.58	0.56
7	0.88	0.84	0.87	0.82	0.15	0.71
8	0.79	0.79	0.86	0.79	0.80	0.92
9	0.88	0.86	0.91	0.80	0.59	0.45
10	0.80	0.84	0.86	0.82	0.78	0.62
11	0.87	0.95	0.87	0.91	0.70	0.66
12	0.79	0.88	0.83	0.88	0.20	0.42
13	0.95	0.80	0.84	0.80	0.68	0.58
14	0.89	0.90	0.89	0.90	0.25	0.71
15	0.89	0.88	0.76	0.84	0.65	0.83
16	0.25	0.85	−0.01	0.84	0.74	0.74
17	0.84	0.89	0.83	0.88	0.80	0.81
18	0.91	0.90	0.90	0.81	0.49	−0.11
19	0.82	0.76	0.86	0.82	0.62	0.68
20	0.86	0.89	0.88	0.78	0.39	0.61
21	0.76	0.81	0.82	0.83	0.34	0.33
22	0.74	0.92	0.74	0.84	0.43	0.76
23	0.94	0.88	0.83	0.88	0.45	0.58
24	0.78	0.81	0.80	0.84	0.65	0.34

28	0.65
29	0.80
30	0.70

25	0.90	0.96	0.85	0.89	0.79	0.82
26	0.88	0.70	0.83	0.78	0.27	0.78
27	–	0.89	–	0.87	−0.29	0.53
28	–	0.88	–	0.85	–	0.59
29	–	0.91	–	0.94	–	0.90
30	–	0.89	–	0.86	–	0.84

Note. b-p = between-participants dataset; w-p = within-participants dataset.

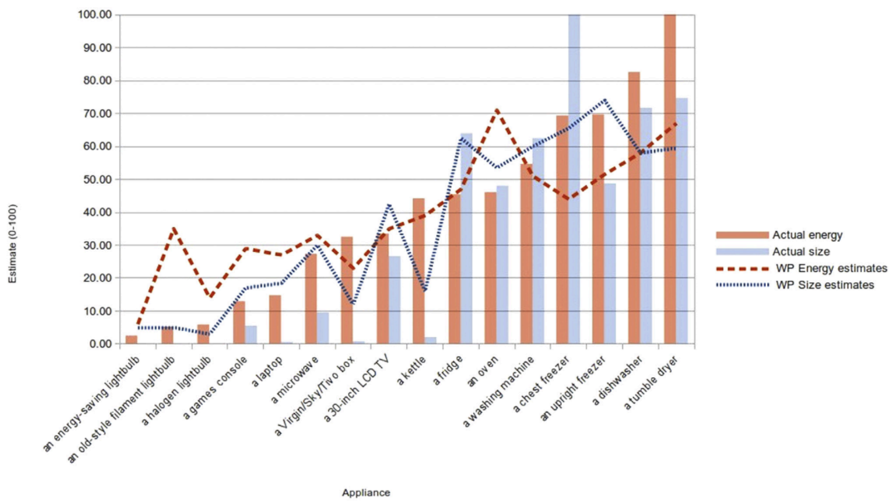


Fig. 2. Actual energy consumption and size of appliances with within-participants average estimates.

energy consumption estimates and actual energy consumption and the correlation coefficients between the same people's estimates of size and energy consumption appeared to vary greatly between individuals (Table C1, column 7, and Table B1). An exploratory correlation of the two sets of coefficients for the same participants showed a strong, positive correlation of $r_s = .82$. This is probably unsurprising as both sets of coefficients were based on the participants' energy consumption estimates. It does confirm, however, that participants whose estimates of size and energy consumption correlated highly also tended to be more accurate in their estimates accurate in their estimates of energy consumption.

4. Discussion

It is essential to understand how householders perceive the energy consumption in their homes if behaviour change interventions and policies are to be effective. Simply providing householders with more and more information does not appear to be helping them to reduce their energy consumption. Identifying the heuristics used in energy consumption judgements would help

Starke, A. D., Willemsen, M. C., & Snijders, C. C. P. (2020). Beyond “one-size-fits-all” platforms: Applying Campbell’s paradigm to test personalized energy advice in the Netherlands. *Energy Research & Social Science*, *59*, 101311. https://doi.org/10.1016/j.erss.2019.101311

define an energy-saving attitude [22], but have hardly discussed policy implications. We consider this a missed opportunity, as a Rasch scale of energy-saving measures, along with the model's formal relation between measures and persons [24], allows policy makers to consider attitudinal differences between individuals in energy-saving advice. For example, such a scale could be employed to estimate an individual's energy-saving attitude and subsequently recommend appropriate energy-saving measures for that attitude. This way, energy policy makers could move beyond the often employed but rather ineffective one-size-fits-all strategies [4,26–28]. In fact, such tailored interventions have shown to be more effective in persuading consumers to adopt energy-saving measures than nondiscriminatory approaches, as well as achieve higher energy savings [3,17,29,30].

To be able to provide tailored advice based on a Rasch scale, two important extensions to earlier work are required. First, in order to have sufficient measures at our disposal to recommend novel measures to consumers, our scale requires a much larger number of energy-saving measures than those used in earlier studies [23,31]. Second, we test whether measuring a small subset of scale measures per person is sufficient to estimate a person's attitude and tailor advice towards it. Eventually, these extensions allow us to evaluate the effectiveness of Rasch-based advice compared to other advice strategies, such as one-size-fits-all approaches.

In the upcoming sections, we first provide some background of the Rasch model by introducing ‘Campbell's Paradigm’. Then, we explain how we use the Rasch model to provide energy-saving advice using a recommender system. Finally, we present two studies: a calibration study in which we construct a Rasch scale of energy-saving measures, followed by a user study that investigates how tailored energy-saving recommendations can be created and how they are evaluated.

2. Theory

Usage of the Rasch model in the current context follows the logic of Kaiser et al. [22], who have presented the Rasch model as an alternative way to conceptualize and measure a person's attitude, a topic heavily debated by social psychologists [32–34].

2.1. Campbell's paradigm

Kaiser et al. [22] propose an attitude theory that is named after Donald Campbell [33]. Rather than using evaluative statements, as in conventional attitude research (e.g. [35]), Campbell's Paradigm draws upon a wider range of responses that intermixes both behavioral self-reports and intentions. It describes an axiomatic connection between a person's attitude towards a certain behavioral goal and the behaviors that person is willing to engage in to achieve that particular goal

If an individual discloses engagement levels for multiple energy-saving measures, it becomes possible to estimate that individual's energy-saving attitude. In turn, one's attitude can predict what other measures are likely to be performed.

An important assumption of Campbell's Paradigm is that these behavioral cost levels hold for each individual and can predict behavior accordingly. However, Kaiser et al. [22] stress that performing a measure with high behavioral costs does not deterministically guarantee the execution of those with lower costs, as there may be contextual irregularities. Campbell's Paradigm accounts for these irregularities through the Rasch model, which formalizes the axiomatic relationship between attitudes and behavioral costs in a probabilistic model.

2.2. The Rasch model

Commonly used in psychometrics and based on item-response theory [39], the Rasch model predicts whether a person performs a particular item or behavior. It does so by modeling a latent trait as a function of the behavioral difficulties of a set of trait items [24]. In an energy-saving context, Rasch captures energy-saving measures and persons onto a one-dimensional measurement scale [22,23]. The level of behavioral costs of a measure is proportional to the number of individuals in a sample performing it, where commonly performed measures yield lower behavioral costs than those performed by fewer persons. Conversely, the strength of a person's attitude increases proportionally with the number of performed scale measures.

The Rasch model used in the current study predicts whether an individual n performs a measure i or not, as a logistic function of the arithmetic difference between that individual's attitude θ and the measure's behavioral costs δ. Eq. (1) shows how an increase in one's energy-saving attitude increases the probability that one performs a certain energy-saving measure [40]. Moreover, the current study assumes that such a probability distribution, referred to as an item-characteristic curve [24], is similarly-shaped for each scale item.

$$P\{X_{ni} = 1\} = \frac{e^{\theta_n - \delta_i}}{1 + e^{\theta_n - \delta_i}} \quad (1)$$

Fig. 1 depicts the Item-Characteristic Curves (ICC's) of three different energy-saving measures, illustrating how the engagement probability (y-axis), attitude (x-axis), and behavioral cost parameters (the curves) relate to each other. The energy-saving attitude θ, expressed in logistic scale units (logits), varies between individuals and leads to different engagement probabilities for the various energy-saving measures. In addition, the behavioral cost level δ of a measure is equal to the 50%-engagement probability point of an ICC. Hence, if a person's energy-saving attitude is equal to the behavioral cost level of an energy-saving measure, then that person has a 50% probability of performing

[31,36,37]. In the conservation context, Campbell's Paradigm postulates that one's attitude for saving energy becomes apparent through the different energy-saving measures a person is willing take [22].

Energy-saving measures form a specific latent class pertaining to the goal of saving energy [23], as long as these measures differ in their execution difficulty [22]. This execution difficulty is operationalized as a behavioral cost level [22], which comprises costs in terms of, among others, cognition, money, and time [38], and can differ substantially between measures. For instance, verbal statements typically come with low behavioral costs (e.g. stating that saving energy is important), while actually installing energy-efficient appliances come with much higher costs (e.g. installing solar PV on one's rooftop requires costs in terms of cognitive effort, money, and time).

Furthermore, Campbell's Paradigm prescribes that persons committed to performing an energy-saving measure carrying high behavioral costs are also likely to perform measures with lower costs [22,36]. For example, an individual who applies thermal insulation, which is a relatively high-cost measure, is also likely to turn off the lights after leaving a room, which is a relatively low-cost measure [23].

that measure. Consider for example a person with an attitude θ of 0.9 logits: Fig. 1 shows that this person has a 50% probability to use a water-saving showerhead (δ = 0.9 logit), but would be much more likely to own double-glazed windows (δ = −1.72 logit), namely 93%.

2.3. Dimensionality of energy-saving behavior

The adequacy of using the Rasch model to describe energy saving and other environmental behaviors finds empirical support in multiple studies [21,41]. In particular, Urban and Ščasný [23] show through a survey on self-reported energy-saving measures in ten OECD countries that the Rasch model outperforms approaches that differentiate between curtailment and efficiency, detailing two main findings. First, a two-factor model does not properly represent patterns of energy-saving behavior, while the one-dimensional Rasch model does have an acceptable model fit. Second, although the average behavioral cost level of efficiency measures exceeds that of their efficiency counterparts, both curtailment and efficiency measures are intermixed as part of the unidimensional Rasch construct. For instance, in some countries, an

reliability α of 0.92, suggesting that the scale's order in terms of behavioral costs is likely to be reproducible [40]. Second, the model had a large item separation of 3.48 and an item mean square close to the identity value (0.98), both indicating that the scale is suitable for measurement [48]. The inferred participant attitudes had a person reliability of 0.59 and a separation of 1.14, which were acceptable values [24], particularly because we only used thirteen measures per person. In addition, the model's fit statistics were comparable to studies which employed fewer items [23].

3.2.3. Dimensionality

We investigated the dimensionality of participants' responses by analyzing the explained variance for both one- and multidimensional constructs, consistent with dimensionality checks in other domains [24]. Using Winsteps software [49], we determined that the one-dimensional construct explained 39.6% of the variance in the data, slightly overfitting the predicted model fit (39.1%). The remaining 60.9% was quantification variance, which is residual variance caused by the Rasch model's estimated probabilities for discrete, dichotomous events (0 or 1).

We checked whether multiple scale measures shared an unexpected response pattern in the residual variance and formed an additional dimension [51]. A principal component analysis on the standardized residuals showed little evidence to expect more than one dimension in our sample, as an additional factor would only result in a trivial increase of 1.8% in the proportion of explained variance. Moreover, measures in these additional dimensions did not seem to form meaningful factors, which further confirmed earlier research that an individual's energy-saving attitude could be assessed on a one-dimensional scale [22,23].

Fig. 2 depicts the distribution of curtailment and efficiency measures across the scale, in terms of their behavioral costs. As in Urban and Ščasný [23], curtailment and efficiency measures formed a single construct but were not uniformly distributed across the one-dimensional scale. This is illustrated by a higher density of efficiency measures on the high-cost end of the scale: curtailment measures (N = 46; M_{cur} = −0.67 logistic units) had on average lower behavioral costs than efficiency measures (N = 33; M_{eff} = 1.08 logistic units), consistent with findings that efficiency measures are on average less likely to be performed than curtailment [7]. However, Table 1 points out that some curtailment measures still had particularly high behavioral costs (e.g. keeping the rear of a refrigerator dust-free, δ = 2.43), while some efficiency measures had very low behavioral costs (e.g. using a laptop instead of a PC, δ = −3.45).

3.3. Conclusion

Study 1 delivered a unidimensional scale of 79 energy-saving measures, suitable for advising a heterogeneous group of persons due its diversity in behavioral cost levels. Consistent with Urban and Ščasný [23], we have found that energy-saving behavior should be described as a one-dimensional rather than a two-dimensional construct, with curtailment and efficiency measures distributed across the entire Rasch scale. The lower average behavioral costs of curtailment measures, compared to their efficiency counterparts, is consistent with earlier findings that consumers are more likely to perform curtailment measures rather than efficiency [9].

Moreover, our study sets forth a behavioral explanation for the (non-)performance of energy-saving measures. Since curtailment and efficiency measures overlap on our behavioral cost scale, a simple dichotomy between those two dimensions is unable to precisely predict whether a measure will be performed or not, much unlike the formal Rasch model. This supports claims in earlier research that the curtailment-efficiency dichotomy lacks empirical validity [5].

The moderate (for persons) and high (for items) scale reliability levels suggest that our estimation procedure has been appropriate. Using only 13 out of 79 scale measures to estimate a person's attitude does not compromise the scale quality in terms of item reliability, and also provides accurate and useful attitude estimates. Moreover, it sets forth a practical approach for applying a Rasch construct in a recommender system, as the attitude estimation procedure is short (in

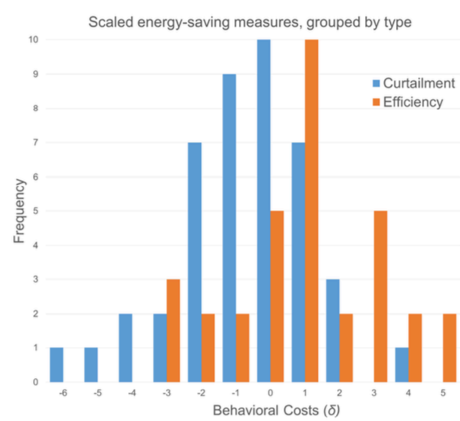


Fig. 2. Distribution of curtailment and efficiency measures fitted on the Rasch scale, relative to their behavioral cost level, confirming that efficiency measures have on average higher behavioral costs, but are intermixed on the scale.

Fig. 3. A partial screenshot of a recommendation list (in Dutch). The user drags a measure to a different position to elicit his/her preference for that measure.

terms of time), as well as restricted (in terms of used measures), which allows multiple scale measures to be presented as novel recommendations to system users. We will explore such tailored energy-saving advice in Study 2.

4. Study 2: Rasch-based energy recommendations

terms of behavioral costs. However, our method of tallying positive responses was much easier to implement in a web-tool, and we found that the resulting estimates still correlated strongly with those determined in a traditional method (cf. Section 4.2.1).

4.1.3. Procedure: recommendation lists

In our second study, we implemented the scale of 79 energy-saving measures, calibrated in Study 1, in a web-based energy recommender system to provide attitude-tailored advice. We investigated users' preferences for measures with different behavioral cost levels, which were either above, below or equal to a user's attitude. Using these evaluations and the probabilities that persons would perform certain measures, we determined to what extent attitude-tailored advice was more appropriate than a non-personalized approach, comparing four different scenarios of energy-saving advice.

The experiment proceeded with two further steps. First, in order to make users more aware of the fact that the system would present tailored advice, users were shown an energy-saving score based on their estimated attitude, which amounted to a value between 1 and 10. Second, following this score, users were presented two consecutive lists of nine randomly-ordered energy-saving measures.

Each recommendation list contained three different types of measures (3 × 3 measures), in terms of their behavioral costs. A list included three measures with behavioral costs that fell below the user's attitude and were likely to be performed (i.e. these had a probability of 75%, or −1 logit compared to the user's attitude), three measures

Starke, A. D., & Willemsen, M. C. (2024). Psychologically Informed Design of Energy Recommender Systems: Are Nudges Still Effective in Tailored Choice Environments? In B. Ferwerda, M. Graus, P. Germanakos, & M. Tkalčič (Eds.), *A Human-Centered Perspective of Intelligent Personalized Environments and Systems* (pp. 221–259). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-55109-3_9
https://mediafutures.no/wp-content/uploads/Starke2024-Book-Chapter-Psych-informed-Energy-RecSys-3.pdf

Table 1 List of energy-saving measures fitted onto the one-dimensional Rasch scale. Measures were used in research conducted in the Netherlands in 2014, which involves gas for heat. Reported are each measure's behavioral cost levels (δ), based on the pre-study ('Study 1' [24, 27]) and the evaluation study ('Study 2' [27])

#	Name of energy-saving measure	δ_{Study1}	δ_{Study2}	Set
1	Save up laundry	−5.73	−3.23	1
2	Take a shower instead of a bath	−4.82	−4.41	1
3	Wash laundry at low temperatures	−3.95	−1.64	1
4	Air-dry laundry	−3.69	−2.93	1
5	Use a laptop instead of a desktop PC	−3.45	−3.62	1
6	Turn off the lights after leaving a room	−2.97	−2.78	1
7	Use public transportation instead of a car	−2.90	−2.52	1
8	Use a woolen blanket instead of an electric blanket	−2.51	−3.03	2
9	Use properly sized cooking equipment	−2.51	−2.69	2
10	Lower the thermostat while away from home	−2.49	−1.92	2
11	Do not put warm things in the fridge	−2.45	−2.40	2
12	Turn off the PC screen after use	−2.20	−0.71	2
13	Close the curtains/shutters in the evening	−2.09	−1.57	2
14	Shift gears at low speeds	−1.89	−2.07	3
15	Cook with a lid on the pan	−1.81	−1.81	3
16	Use energy-saving bulbs (CFL's)	−1.75	−1.31	3
17	Double-glaze windows	−1.72	−1.24	3
18	Air rooms for 20 min daily	−1.51	−1.21	3
19	Cook on gas stove instead of electric	−1.36	−2.23	3
20	Lower the thermostat one degree	−1.25	−0.47	4
21	Set thermostat to 14 °C before going to bed	−1.20	−0.90	4
22	Do not defrost food using a microwave	−1.18	−0.52	4
23	Turn off the TV instead of stand-by	−1.06	−0.74	4
24	Maintain correct tire pressure	−0.94	−0.27	4
25	Stir-fry food	−0.91	−0.62	4
26	Turn off the PC at the main switch	−0.81	−0.21	5
27	Turn off the coffee machine completely	−0.57	−1.30	5
28	Turn off the dishwasher after use	−0.57	−0.37	5
29	Insulate the cavity wall	−0.51	0.50	5
30	Turn off the washing machine completely	−0.49	−0.22	5
31	De-ice the fridge	−0.46	0.59	5
32	Unplug chargers	−0.32	−0.44	6
33	Take short showers	−0.29	0.52	6
34	Hand-wash dishes (no dish washer)	−0.22	−0.72	6
35	Configure PC power management	0.00	0.29	6
36	Shorten PC/laptop stand-by time	0.01	−0.43	6
37	Air clothes instead of washing them	0.07	−0.39	6
38	Clean the cooker hood suction filters	0.14	0.29	7
39	Place fridge in a suitable position	0.18	−0.14	7
40	Use LED lighting	0.37	0.38	7
41	Decalcify your coffee machine and/or kettle	0.40	0.35	7
42	Sweep instead of using a vacuum cleaner	0.43	0.40	7
43	Use a smart thermostat	0.47	−0.11	7
44	Put a weather strip on the door	0.47	0.19	8
45	Use a HE boiler or CHP	0.47	0.98	8
46	Use household devices without displays	0.48	2.67	8
47	Use an 'A+' energy-class fridge	0.51	−0.09	8
48	Install motion sensors	0.51	−0.02	8
49	Insulate floors	0.56	0.29	8
50	Use a mini PC instead of desktop computer	0.59	3.89	9
51	Make coffee without using a heating plate	0.74	−0.84	9
52	Decalcify the washing machine	0.75	0.59	9
53	Use green power	0.85	0.22	9
54	Turn off the fridge while on holiday	0.87	1.84	9
55	Turn off the PC when away from keyboard	0.88	−0.74	9
56	Use a water-saving showerhead	0.90	0.34	10

(continued)

Table 1 (continued)

#	Name of energy-saving measure	δ_{Study1}	δ_{Study2}	Set
56	Use a water-saving showerhead	[illegible]	[illegible]	10
57	Put your shirts briefly in the laundry dryer instead of ironing them	0.96	1.15	10
58	Cover the windscreen of your car	0.96	0.81	10
59	Replace dimmer switches	0.99	1.04	10
60	Use an 'A-label' energy-saving laundry dryer with a heat pump	1.17	1.36	10
61	Use day and night tariffs	1.21	0.75	10
62	Set boiler temperature to 65 °C	1.24	1.04	11
63	Set the mixing valve at a lower temperature	1.31	1.17	11
64	Put weather strips on the windows	1.46	0.59	11
65	Insulate hot water pipes	1.53	0.79	11
66	Clean the water heater	1.63	1.26	11
67	Install a door closer	2.34	1.39	11
68	Turn off the oven before the end of cooking time	2.40	2.27	12
69	Keep the rear of the fridge dust-free	2.43	1.25	12
70	Apply heat reflection foil to radiators	2.77	3.46	12

(continued)

Table 1 (continued)

#	Name of energy-saving measure	δ_{Study1}	δ_{Study2}	Set
71	Replace a radio alarm with a 'classic', unplugged alarm clock	2.88	3.51	12
72	Use a cabled telephone instead of a handheld phone	2.91	2.49	12
73	Install solar PV	3.17	1.60	12
74	Install a solar boiler	3.26	2.53	13
75	Slow down the PC processor	3.70	3.47	13
76	Use a pull bell instead of an electrical bell	3.82	3.20	13
77	Wash using a 'hot-fill' washing machine	4.04	2.36	13
78	Use software for dynamic energy use in a laptop or PC	5.18	0.52	13
79	Erect a small wind mill to produce electric energy	5.49	4.42	13

This effect is also depicted in Fig. 4, where negative differences indicated relatively difficult measures. These were, thus, ranked much lower. Second, we observed a *negative* effect of kWh savings on the predicted ranking, indicating that users were actually less likely to adopt measures that saved a lot of energy. This suggested that kWh savings were not a factor in user decision-making, but that expected effort or difficulty seemed to be a much more important predictor. Third, we observed small ranking bias, as measures that were ranked higher at the start were also more likely to be ranked higher in the end. In contrast, whether a measure was of the curtailment type did not affect the final ranking.

Finally, the data collected in the evaluation study are reported in Table 1. It also includes an updated scale using the data obtained in Study 2, which led to changes in the δ values, but only a few values were changed significantly. For those measures, such as "Use a mini PC instead of desktop computer", it was advisable to exclude it from the scale in further studies.

3.2.3 Implications

It has emerged that users prefer relatively easy-to-perform measures, within the attitude-tailored advice context. Based on the Rasch scale used, there is a trade-off between feasibility and novelty when generating advice. On the one hand, the behavioral costs of measures should not exceed a user's attitude too much, because this might prevent a user being able or willing to perform a measure at all. On the other hand, measures should be novel, in the sense that the user does not already perform them, which would make the advice redundant. In Starke et al. [27], further analysis reveals that tailored advice is likely to be more effective than simply presenting 'popular' or 'middle-of-the-scale' items, but this needs to be validated further in

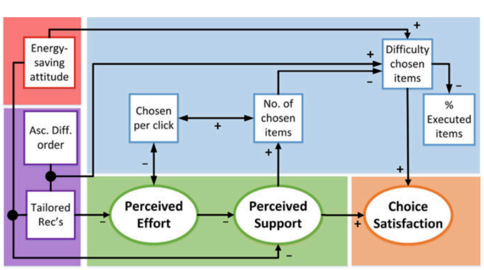


Fig. 6 Structural Equation Model (SEM) for the smart default study [25]. Relations between aspects resemble correlations. Coefficients and standard errors are omitted for simplicity. Details

aspects resemble correlations. Coefficients and standard errors are omitted for simplicity. Details are deported in Starke et al. [25]. Colors follow the guidelines of Knijnenburg et al. [61]: Objective aspects are purple, observed variables are in blue, personal characteristics are in red, perception aspects in green, and experience aspects in orange. Difficulty is considered synonymous for behavioral costs

found in our analysis with $N = 209$ users, as tailored recommendations led a reduced effort perceptions, which in turn led to higher levels of perceived support and choice satisfaction. This is also depicted in a simplified Structural Equation Model, which is reported in Fig. 6, while full mathematical details can be found in Starke et al. [25]. These findings showed that a psychologically informed algorithm can lead to an improved user experience, as well as affect user choices.

A structural equation model (SEM) analysis was performed [25], based on the evaluation framework by Knijnenburg and Willemsen [74]. Multiple interaction effects between the fit score and either the recommended difficulty or user attitude were found (cf. Fig. 8). First, users with a strong attitude benefited less from the fit

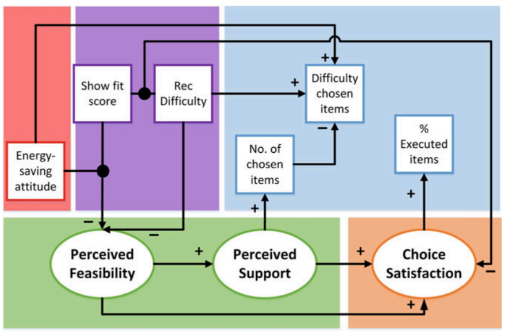


Fig. 8 Structural Equation Model (SEM) for the Fit Score study [25]. Relations between aspects resemble correlations. Coefficients and standard errors are omitted for simplicity. Details are deported in Starke et al. [25]. Colors follow the guidelines of Knijnenburg et al. [61]: Objective aspects are purple, observed variables are in blue, personal characteristics are in red, perception aspects in green, and experience aspects in orange. Difficulty is synonymous for behavioral costs

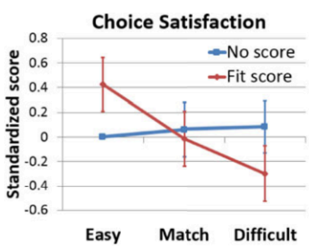


Fig. 9 Standardized scores for choice satisfaction in the fit score study [25], as a function of the research design: the attitude-cost difference of the recommended tab (easy $= +1$, match $= +0$, and difficult $= -1$ logit), and the presence of a fit score. Image adapted from Starke et al. [25]

score, as it decreased their perceived feasibility of the recommended measures. Second, higher behavioral cost or difficulty levels of advice also decreased feasibility, which was not mitigated by the fit scores. Third, there was a negative interaction effect between fit score and recommendation difficulty on choice satisfaction. Taken together, it seemed that the fit score was particularly unproductive for users with high ability levels. Measures that were relatively challenging in an absolute manner were presented with high fit scores, which high-ability users probably did not expect or found feasible. In contrast, fit scores were beneficial for users with a low attitude.

To contextualize the effects depicted in the SEM, we examined the effects on choice satisfaction in Fig. 9. It shows a flat line for the no-fit score condition, but a clear 'easiness' preference in the fit score condition that is in line with the 2020 study from Starke et al. [27]. The salience of how well a measure matched a user, in combination with the difficulty signposts, seemed to have backfired, as it did not match a user's feasibility perception. This is an example of how a psychologically informed design of the interface can undermine the algorithmic rationale.

This study has made clear that it is challenging to overcome the tendency of users to prefer relatively easy energy-saving measures. Simply explaining the algorithm to the user, as is done in many recommender studies [103], seems to backfire in this domain. In our interface, the persuasive strategy to use a fit score was not able to overcome preferences triggered by the tailoring strategy. Hence, it seemed that the tailoring approach of the recommender system (i.e., 'does the item really fit me?') was a more important determinant of user choice and evaluation outcomes than the persuasive elements presented in the interface (e.g., 'is the item promoted?'). In lieu of these findings, we examined the possibilities of using a different type of persuasive

Van Den Broek, K. L., & Walker, I. (2019). Heuristics in energy judgement tasks. *Journal of Environmental Psychology*, *62*, 95–104. https://doi.org/10.1016/j.jenvp.2019.02.008

Appendix A

Table 1
Percentage of selection of heuristics, mean number and standard deviation (SD) of selected heuristics per participant and total number of selections per appliance

	Fridge	Oven	Phone charger	Microwave	Lightbulb	Hair dryer	Kettle	Tumble dryer	Laptop	Washing machine
Task complexity	2.13	1.53	6.07	4.43	5.26	2.96	1.95	4.39	10.57	5.34
Task size	4.51	3.06	11.39	4.43	4.24	3.55	6.17	7.84	5.65	8.26
Number of tasks	1.88	2.00	2.28	1.33	1.53	1.18	0.97	2.26	5.95	3.94
Energy label	6.14	2.47	1.90	2.36	5.43	1.48	1.62	3.44	2.53	4.32
Brand	1.75	1.18	1.33	1.62	3.90	2.66	2.11	2.02	3.42	3.05
Number of components	1.63	0.94	2.28	1.62	1.70	1.48	1.30	2.49	4.17	1.65
Size	8.77	4.00	9.30	3.10	5.77	3.25	3.41	7.96	3.42	5.59
Heat	3.51	16.49	0.76	11.52	5.26	15.98	17.69	10.93	2.38	7.75

Table 1 (*continued*)

	Fridge	Oven	Phone charger	Microwave	Lightbulb	Hair dryer	Kettle	Tumble dryer	Laptop	Washing machine
Cold	14.29	1.30	0.19	1.92	0.34	0.89	0.65	0.59	0.45	1.40
Hot device	4.51	6.60	3.04	3.69	7.81	8.43	4.87	2.73	7.74	1.78
Speed	2.38	6.95	10.06	10.34	1.87	6.21	10.71	5.82	3.42	6.23
Time switched on	8.65	9.54	11.76	9.60	12.73	10.06	6.01	8.43	10.71	9.53
Necessity	2.76	2.47	3.42	1.62	4.58	2.51	2.27	2.26	3.87	2.67
Costs	1.38	1.18	0.57	1.03	1.87	0.74	1.46	1.90	1.04	1.52
Phase	2.76	3.18	0.38	0.74	0.34	1.33	1.79	0.95	0.74	1.78
Heat-up time	0.88	5.18	0.57	2.95	0.85	3.85	5.84	2.26	1.04	1.78
Heat-up	0.50	3.06	0.38	1.03	0.17	1.92	1.14	1.78	0.89	1.65
Usage pattern	1.13	3.42	2.85	3.10	4.07	3.55	3.08	3.21	4.91	3.05
Sustenance	2.01	2.47	0.38	1.18	0.68	2.22	0.81	2.14	0.89	3.43
Watt	1.63	1.18	2.66	4.28	7.64	2.51	3.41	1.31	1.64	1.40
Received wisdom	3.51	3.18	2.66	2.66	4.07	2.81	5.19	4.87	2.08	2.92
Energy efficiency	2.76	1.18	1.14	1.33	3.40	0.30	0.97	1.78	1.49	1.65
Unknown source	2.26	1.77	3.61	1.77	2.38	1.92	1.46	2.14	2.53	1.65
Function dissimilarity	1.88	1.41	2.66	1.33	1.02	1.63	0.81	1.31	1.34	0.76
Function similarity	1.13	1.30	0.57	2.07	1.02	0.89	1.30	1.07	0.45	1.78
Category	0.25	0.35	0.57	0.44	0.17	0.30	0.16	0.36	0.45	0.13
Perceived energy intensity	5.39	4.95	6.64	8.12	6.28	6.21	5.52	4.99	4.76	4.45
Task/size ratio	2.38	1.88	3.61	2.36	1.36	1.92	1.62	1.66	2.68	1.65
Perceived power	3.88	4.12	4.74	6.35	3.06	5.33	4.22	4.16	4.32	4.45
Activity	3.38	1.65	2.28	1.62	1.19	1.92	1.46	2.97	4.46	4.45
Mean number of heuristics (SD)	3.29 (2.55)	3.48 (3.14)	2.13 (2.14)	2.73 (2.70)	2.41 (2.32)	2.73 (2.90)	2.48 (2.55)	3.40 (3.51)	2.71 (3.00)	3.27 (3.62)
Total count	798	849	527	677	589	676	616	842	672	787

2.1. *Method*

A qualitative approach was taken to map the energy judgement heuristics, potentially allowing any heuristic to be uncovered in this study. This is in contrast with previous studies that assessed whether the rating of an attribute could be statistically related to the energy judgement (Attari et al., 2010; Baird & Brier, 1981; Cowen & Gatersleben, 2017; Schuitema & Steg, 2005), and thereby only investigated the use of heuristics that were hypothesised a priori.

To prompt the use of energy judgement heuristics, groups of participants conducted a task in which household appliances were ranked by their perceived energy use. Participants were instructed to only consider the energy use of each appliance when in use for one minute, thereby factoring out differences in the frequency and duration for which the appliances tend to be used. It is acknowledged that the energy use of appliances is also strongly determined by the use of the appliance, potentially limiting the ecological validity of the decision-making process in this task. However, the fixed-time instructions were necessary to avoid extensive discussions on the use of the appliance, as this is likely to differ across participants. The current task was therefore the preferred method to measure which other factors are considered when judging energy use of appliances.

The rank-order task was designed to not include a reference point, as this was found to be problematic in previous research due to the use of an anchoring and adjustment heuristic (Frederick et al., 2011). Furthermore, this task allowed the use of heuristics to occur spontaneously without explicitly prompting participants to use certain heuristics, which could make participants aware of the observation of their decision-making process and the research objectives. Participants were instructed to conduct the task together, meaning the rank-order task functioned to generate discussion about the methods that could be used to estimate the relative energy consumption of the household appliances and to make implicit ideas about energy consumption explicit through interpersonal debate. Note that we do not claim this method captures all participants' heuristics, as participants may not report on heuristics that they are not aware of using or that they do not perceive as valid heuristics. However, this was not the goal; rather, we sought to estimate the overall extent of heuristic use rather than a firm quantification.

Table 1
Overview of themes and codes (number of instances OBSERVED/NUMBER OF INSTANCES SELF-REPORTED).

Theme	Description	Subthemes	Description	Example
Task (36/5)	Aspects of the device's task(s) are employed	• Task complexity (6/1) • Task size (30/4)	• Devices that carry out complex tasks consume more energy • Devices that complete several tasks (either simultaneous or successive), or large tasks, consume more energy	• "Uhm, phone charger, not much? It's easy isn't it?" • "But then, surely, coffee machine, has gotta be above kettle, because it's doing more things, than a kettle"
Knowledge (24/1)	Prior understanding of the energy use	• Wattage (5/1) • Received wisdom (18/0) • Energy label (1/0)	• Devices that use a lot of Wattage consume more energy • Knowledge about the energy consumption of the device that stems from public discourse or an unspecified source • Devices that have an energy label use more energy	• "A microwave is about 800 Watt, that's the only thing I know." • "Portable heater take up loads of energy, someone told me that." • "Because fridges have those things where they have to tell you how much energy they use and stuff whereas phone chargers … you know"
Force (21/10)	Perception of the force of the device	• Perceived energy intensity (8/5)	• Devices that are less energy intense use less energy	• "I think they'll be quite energy intensive so let's put it there [pointing to the top of the ranking-order]."

		• Perceived power (4/1) • Activity (8/3) • Task/size ratio (1/1)	• Devices that are more powerful use more energy • More active devices use more energy • Devices that are small but conduct a large task use a lot of energy	• "Toothbrush is quite powerful" • "They are not quite, if you know what I mean, they are not active as these things" • "Because that heats up everything around it, and it's only a small thing, so it's probably more likely to create more heat quicker [others agree] than'"
Physical features (48/5)	Physical characteristics of the device	• No. of components (7/0) • Type (24/0) • Size (9/5) • Charging needs (8/0)	• Devices with a lot of components use more energy • Devices from some brands or certain type of devices are more energy consuming • Larger devices consume more energy • Devices that charge other devices use more energy	• "Because you have a DVD player in your laptop, so a laptop with a disc driver is going to have more than a DVD player." • "Yes, it depends on the hoover. [..] Maybe a Henry hoover wouldn't be quite as bad" • "Well, maybe the smallest things use the least" • "Phone charger, well chargers might need quite a bit because they're charging something."
Relative standing (53/2)	The energy use of the device is compared to other devices	• Category (29/0) • Function (24/2)	• Appliances that are semantically related to each other consume similar levels of energy use • Devices with similar functions consume same levels of energy while devices with different functions consume different levels of energy.	• "DVD player and TV would be quite similar I think" • "Uh, I don't think an iron is too bad, because it's just heating up like straighteners, and hair straighteners aren't too bad."
Temporal patterns (49/4)	Time-based aspects of the appliance are used	• Speed (12/2) • Time switched on (37/2)	• The faster the device completes its task, the more energy the device consumes • Devices that are switched on for a longer period of time consume low levels of energy	• "Kettle would, kettle would use a lot. Because it heats up water really quickly doesn't it?" • "I think, it must be like, fridge freezer, must not use a lot because they are on all the time"
Multiple consumption modes (37/0)	Consideration of the variability of the process of the task of the devices	• Sustenance (9/0) • Utility phase (2/0) • Settings (8/0) • Heating up phase (18/0)	• Devices that 'keep up the heat' or movement consume more energy • Device use less energy in the utility phase compared to its use in a 'preparation phase' • When the device can be set on a higher unit (e.g. higher temperature) the device uses more energy • Devices that have an initial heating up phase consume more energy than devices that do not	• "Yeah, they have to like keep up the heat" • "Because you have to warm up the iron, and then you stop kind of" • "Yes, it really depends on what temperature you are using it at" • "Yeah, because that just goes like instantly hot, doesn't it? So shall we put electric hob up a bit?"
Temperature (33/4)	Temperature features of the appliance are employed	• Heat (31/4) • Cold (2/0)	• The more a device produces heat to heat up air or water or itself, the more energy it consumes • Devices that reduce the temperature of an element such as air or water were consume high levels of energy	• The ones that produce heat, are gonna be high up, aren't they, they use a lot of energy, like things that produce heat use the most, so that's going to be high up." • "They have to keep it at a very cold temperature"
Experience (4/0)	Considering the experience with the device	• Cuts out the fuser (4/0)	• Devices that have previously cut out the fuse box consume a lot of energy.	• "So I [think] high, because in my room, always, it always cut's out the fuse … so …"

Cowen, L., & Gatersleben, B. (2017). Testing for the size heuristic in householders' perceptions of energy consumption. *Journal of Environmental Psychology*, *54*, 103–115. https://doi.org/10.1016/j.jenvp.2017.10.002

Table A1
Annual UK energy consumption and actual volume of appliances with participants' median estimates of energy and size.

Appliance	Actual Energy[a]	Actual Volume[b]	B-P Estimates		W-P Estimates	
			Energy	Size	Energy	Size
an energy-saving lightbulb	2.45	0.07	15.00	5.00	6.00	5.00
an old-style filament lightbulb	5.21	0.05	40.00	6.00	35.00	5.00
a halogen lightbulb	5.83	0.03	34.00	5.00	14.00	3.00
a games console	12.88	5.48	35.00	20.00	29.00	17.00
a laptop	14.72	0.53	36.00	20.50	27.00	18.50
a microwave	27.30	9.52	37.50	35.00	33.00	30.00
a Virgin/Sky/Tivo box	32.52	0.66	27.00	17.50	23.00	12.00
a 30-inch LCD TV	33.44	26.62	44.00	41.00	35.00	42.50
a kettle	44.17	2.04	39.00	11.00	39.00	16.00
a fridge	45.40	63.85	50.00	67.00	47.00	62.50
an oven	46.01	48.03	57.00	67.50	71.00	53.50
a washing machine	54.60	62.44	60.00	69.50	51.00	60.00
a chest freezer	69.33	100.00	45.00	78.50	44.00	65.50
an upright freezer	69.63	48.74	57.00	68.50	51.50	74.00
a dishwasher	82.52	71.69	50.00	69.00	58.00	58.00
a tumble dryer	100.00	74.64	65.00	69.50	67.00	59.50
a bathroom extractor fan		0.02	23.00	13.50	17.50	10.00
a central heating boiler		22.31	64.00	58.50	75.00	52.00
a DAB (digital) radio		0.68	16.00	14.00	14.00	11.50
a free-standing electric heater		27.72	68.50	30.00	61.50	30.00
a hairdryer		1.67	30.00	10.50	32.00	11.50
a lawnmower		32.86	41.00	44.00	29.50	46.50
a mobile phone		0.01	20.00	6.00	18.00	5.00
a smoke alarm		0.20	7.50	7.00	3.00	5.00
a tablet/iPad		0.06	19.00	11.50	21.00	9.50
a vacuum cleaner		28.58	32.00	36.50	37.00	31.00
a wifi/internet router		0.62	22.00	11.00	15.00	7.00
an electric blanket		3.86	35.00	22.50	33.50	20.00
an electric shower		0.92	49.50	29.00	56.00	24.50
an iron		1.33	32.00	13.00	26.50	13.50

Note. B-P = between-participants dataset; W-P = within-participants dataset. [a]The actual energy consumption of each appliance was standardised so that the highest consuming appliance consumed 100 units of energy. The *tonnes of oil equivalent* were multiplied by 3067.484662577. The number of units is rounded to 2 decimal places for clarity in this table. [b]The actual size of each appliance was standardised so that the largest appliance was 100 units in size. The cm^3 volume was multiplied by 0.000238039.

Lundberg, D. C., Tang, J. A., & Attari, S. Z. (2019). Easy but not effective: Why "turning off the lights" remains a salient energy conserving behaviour in the United States. *Energy Research & Social Science*, *58*, 101257. https://doi.org/10.1016/j.erss.2019.101257
https://www.szattari.com/publications

Easy but not effective: Why "turning off the lights" remains a salient energy conserving behaviour in the United States
Daniel C. Lundberg, Janine A. Tang, and Shahzeen Z. Attari (2019) *Energy Research & Social Science*, 58.

- Survey
- Data (xlxs)

Table 1
Categorized responses to two open-ended questions about the single most effective thing that participants *currently* do and *could* do to save energy in their lives (N = 1418).

Categories	Percent of Responses		Curtailment (C) or Efficiency (E)
	Currently Do	Could Do	
Turn off the lights	36.3	6.6	C

Adjust thermostat	15.3	13.7	C
Replace incandescent light bulbs with CFL/LED bulbs	7.8	3.9	E
Sleep/relax more	7.1	7.7	–
Use appliances/electronics less	5.2	9.3	C
Unplug or turn off appliances	3.5	5.6	C
Broadly "use less energy"	3.0	4.4	C
Drive less	2.9	3.5	C
Conserve water	2.5	4.1	C
Use efficient appliances	2.5	6.4	E
Walk more	2.3	1.6	C
Use public transportation	2.2	1.9	C
Recycle	1.4	2.1	C
Use more efficient or electric vehicles	1.4	3.0	E
Other	1.1	3.1	–
Eat sustainably	0.9	0.9	C
Improve household envelope efficiency	0.9	4.7	E
Bike more	0.7	1.4	C
Use renewable energy	0.7	11.7	–
Carpool/rideshare	0.6	1.1	C
Lower water heater temperature	0.6	0.1	E
Hang laundry/Reduce dryer use	0.5	–	C
Nonsense answers	0.5	1.5	–
Work from home	0.2	0.1	C
Compost	0.1	0.1	–
Unsure	–	0.8	–
Limit airline use	–	0.4	C
Not living/Dying	–	0.3	–

Table 2
Open-ended coded responses explaining how participants recommended turning off the lights or replacing incandescent bulbs with efficient bulbs to a friend *(N = 1418)*.

Categories	Total (%)	By Response (%)	
		Turn off the Lights	Efficient bulbs
Efficiency of bulb key factor	13.7	0.6	17.5
Saves energy while lights are on	12.1	0.9	15.3
No energy is used when lights are off	11.3	48.1	0.5
Longer term savings or savings achieved quickly	8.5	3.7	9.9
Already practicing one action, so must adopt alternative	5.6	0.6	7.1
Action is "better"	4.7	5.0	4.6
Saves money	4.2	4.3	4.2
What works best for me works best for them	4.0	5.0	3.7
Considered situational context	3.9	4.3	3.8
Influenced by provided infographic	3.7	0.0	4.8
Restated given answer	3.7	4.0	3.6
Decided based on previous education	3.7	2.8	3.9
Practical/feasible, no life style change necessary	3.5	1.2	4.2
Ease/difficulty of remembering action	3.1	0.3	3.9
Felt right	2.9	4.3	2.5
Other	2.5	4.7	1.9
Would recommend both	2.1	1.2	2.4
Guessed	1.9	1.2	2.1
Habit	1.8	2.8	1.5
Given reason does not make sense	1.3	2.5	1.0
Easy to do	1.1	0.9	1.1
Relied on logic	0.5	0.6	0.5
Safer/Healthier	0.1	0.6	0.0
Total Percent of Responses	**100**	**22.7**	**77.3**

Table 3
Attribute statements and means. *Scale: 1 = strongly disagree to 5 = strongly agree.* Given the multiple comparisons, the Bonferroni corrected alpha is 0.0025 (α = 0.05/20).

Label	Attribute	Means		Paired *t* test	
		Turn off lights	*Efficient bulbs*	*t* value	*p* value
Able	I am able to do this where I live	4.6	4.5	6.11	< 0.0001
Advocacy	I do this because of public advocacy (advertisements, media, etc.)	2.6	2.9	−8.81	< 0.0001
Carbon	This significantly reduces my carbon footprint	3.9	4.0	−5.55	< .0001
Easy	This is easy to do	4.5	4.2	12.12	< 0.0001
Effective	This is the most effective method I know to save energy	3.3	3.4	−1.86	0.0624
Effort	This requires too much effort	1.6	1.9	−9.44	< 0.0001
Environment	This helps the environment	4.3	4.3	4.14	< 0.0001
Ethical	This is ethical to do	4.2	4.2	2.21	0.0275
Everyone	Everyone else does this, so I do it too	3.1	2.8	11.98	< 0.0001
Example	This will set a good example for people around me	4.0	3.8	7.29	< 0.0001
Future	This will help future generations	3.9	4.1	−8.26	< 0.0001
Good	Doing this makes me feel good	3.9	3.8	0.64	0.5235
Guilty	I will feel guilty if I do not do this	3.7	3.2	14.91	< 0.0001
Habit	This is my habit	4.4	3.4	25.78	< 0.0001
Logical	This is logical to do	4.6	4.4	8.09	< 0.0001
Longer	This will make my light bulbs last longer	4.3	4.3	0	1
Money	This saves me money on my electricity bill	4.4	4.4	0.92	0.3554
Pressure	Friends pressure me to do this	1.9	1.8	3.56	< 0.0001
Taught	I was taught to do this	4.4	3.1	36.03	< 0.0001
Time	This takes too long to do	1.8	2.0	−5.03	< 0.0001

the lights has been the most salient energy-saving behavior for at least thirty years, participants today are aware that it may not be the most effective energy-saving action they could do. We also acknowledge that

Table 4
Responses by participants explaining *why* they think turning off the lights is the most common response when asked how best to save energy.

this finding could represent a conversational norm of not repeating an answer already provided for the pervious question [46,52].

When participants were provided with just two options to recommend to a friend for energy conservation: "turning off the lights" or "replacing incandescent light bulbs with more efficient bulbs," 77% of participants recommended replacing incandescent light bulbs with more efficient lamps. Only 23% of participants choose "turning off the lights."These recommendations of efficiency rather than curtailment deviate from responses in the original open-ended questions, but are confirmed by responses asking participants to choose between

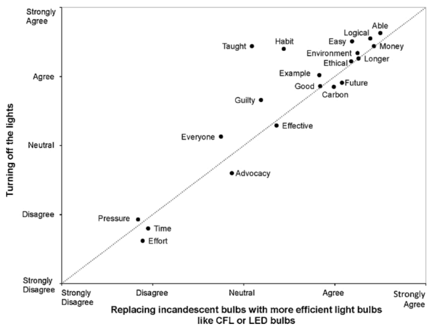


Fig. 2. Mean barrier and motivation attribute ratings associated with replacing incandescent light bulbs with more efficient lights plotted on the x-axis; mean barrier and motivation attribute ratings associated with turning off the lights plotted on the y-axis. The diagonal dotted line indicates when the attributes

Category	Percent of Responses
Easy to do	26.6
Taught to do this	18.1
Lack of knowledge	6.2
Common behavior, everyone does this	6.1
No energy is used when lights are off	6.1
Effective	4.4
First response they think of	4.3
Money is a key factor	3.5
Habit	3.3
Tangible action	2.7
Other	2.6
Age old/cultural knowledge	2.5
Participant's answer did not make sense	2.4
Logical	1.7
Media advocacy	1.7
Turning off the lights is the best action	1.6
Encountering lights left on jogs memory	0.9
Easy to remember	0.8
Unimportant	0.8
Did not know	0.8
No special tools or knowledge needed	0.7
No additional resources needed	0.6
Quick, time to do action	0.6
Relevant to their lifestyle	0.5
Have not yet adopted new, efficient appliances	0.4
Able to do action	0.4
Feels good	0.4
Reported action as "good"	0.1
Immediate savings	0.1
Total	**100**

curtailment and efficiency actions more broadly, where 67% of participants state that replacing an appliance with a more efficient model saves more energy than reducing how often you use an appliance. In initial responses, 36% of participants listed "turn off the lights" as the most effective energy-saving action they *currently* do, while only 8%

fective.

3.2. Perceived differences in barriers and motivations of turning off the lights and replacing incandescent bulbs with CFL or LED bulbs

Paired *t* tests between curtailment and efficiency values revealed significant differences for most attributes of energy-saving barriers and motivations (see Table 3). Fifteen of twenty attributes tested were statistically significant using a Bonferroni corrected alpha of 0.0025 ($\alpha = 0.05/20$). Non-statistically significant attributes were: (1) "this saves me money on my electricity bill"; (2) "this makes my light bulbs last longer"; (3) "doing this makes me feel good"; (4) "this is ethical to do"; and (5) "this is the most effective method I know to save energy." Table 3 presents means for each attribute in both the curtailment and efficiency scenarios, along with label keys and paired *t* test results.

Attribute ratings were generally grouped by influence type (see Fig. 2). Motivations, such as such as "easy", "able", and "good", were

3.3. Examining why turning off the light is so persistent and hard to correct

3.3.1. Self-reported explanations

Participant responses led to 29 coded categories when asked why "turn off the lights" remains the most frequent response to the question, "What is the single most effective thing you could do to save energy" (See Table 4). Two coders categorized these responses yielding strong interrater reliability; Cohen's $\kappa = 0.80$. "This is easy to do" (26.6%) and "I was taught to do this" (18.1%) were the two most common responses. As one participant put it, "*Probably because it is the easiest thing to do and that is what most of us were taught growing up by our parents.*" Together, these two factors address why participants think this action is popular and why it is thought to be effective. Other factors seem related to these perceptions: "a lack of knowledge" (6%) could be associated with "I was taught to do this" as both actions pertain to energy education. Some saw turning off the light's widespread adoption ("common behavior, everyone does this") as proof that it must be effective (6%). The low cost of turning off the lights ("money is key factor") was the primary

Table 5
Logistic regression predicting listing turning off the lights as the most effective action in the opening question.

Predictor	Scale of Variable	Estimate	Wald χ^2	Odds ratio estimate
Intercept	Logit scale	−0.33	0.30	
Frequency of turning off the lights	1–4 (hardly ever to always)	0.25**	6.7	1.30
Percent of efficient bulbs in home	0–100	−0.0083***	19.5	0.99
New Ecological Paradigm	1–5 scale	0.031	0.11	1.03
Numeracy score	0–7 scale	−0.032	0.94	0.97
Political affiliation	1–7 (very liberal to very conservative)	0.0078	0.041	1.01
Male	0 = female; 1 = male	−0.25*	4.0	0.78
Age	18–78	−0.025***	20.5	0.98
Engineering degrees	0 = no; 1 = yes	−0.40*	4.4	0.67
Level of Education	1–6 (Some schooling, no diploma to graduate degree)	−0.095	2.6	0.91
Income	1–7 (0 to greater than or equal to $200,000)	0.08	1.8	1.08
Rent	0 = no; 1 = yes	0.064	0.25	1.07
Electricity bill	1–9 (under $20 to above $200)	0.90*	6.3	1.09

Odds estimates predict the likelihood of participants choosing option of "turning off the lights." Excluded responses of "other" in Male, and Rent; excluded "do not know," "not applicable," and "I don't pay my bill" in Electricity bill giving N = 1309.

SURVEY

Dear Participant,

Please complete this survey on a relevant public policy issue. The survey is anonymous, and no one will know what answers you give. This brief survey should take no more than 10 minutes to complete Thank you for your time and help with this effort.

Sincerely,
Dr. Shahzeen Attari
Indiana University Bloomington

{Page Break}

What is the single most effective thing you **currently do** to save energy in your life? {Text Box}

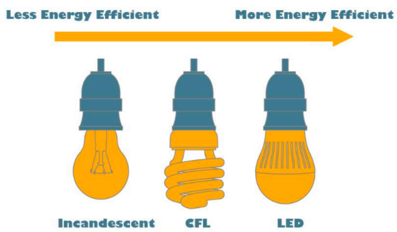
____

What is the single most effective thing you **could be doing** to save energy in your life? {Text Box}

____

{Page Break}

During this survey, please keep the infographic below in mind. Incandescent light bulbs are less energy efficient than CFL (compact fluorescent light) bulbs, and CFL bulbs are less energy efficient than LED (light emitting diode) bulbs.



(Page Break)

Assume a friend of yours wants to know which of the two actions below saves the most energy over the course of a month. Which one would you tell them saves the most energy?

Always turning off the lights when leaving a room	Replacing incandescent light bulbs with more efficient light bulbs, like CFL and LED bulbs

(Page Break)

How did you choose your previous answer?

As a reminder, you were telling a friend which option saves the most energy over the course of a month: turning off the lights or replacing incandescent light bulbs with more efficient light bulbs.

____

{randomized; efficiency attribute section and curtailment attribute section appear in different orders equally}

Now think about the action of **turning off the lights.**

Please state how strongly you agree or disagree with each statement below.

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
This is easy to do					
This saves me money on my electricity bill					
I am able to do this where I live					
I was taught to do this					
This is my habit					
This helps the environment					
This will make my light bulbs last longer					
This significantly reduces my carbon footprint					
Everyone else does this, so I do it too					
I do this because of public advocacy (advertisements, media, etc.)					

{Page Break}

Continue thinking about the action of **turning off the lights.**

Please state how strongly you agree or disagree with each statement below.

Now think about the action of **replacing incandescent light bulbs with more efficient light bulbs, like CFL and LED bulbs.**

Please state how strongly you agree or disagree with each statement below.

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
This is easy to do					
This saves me money on my electricity bill					
I am able to do this where I live					
I was taught to do this					

{Page Break}
{A/B randomized}
For each question below, read the two options presented and choose the option that you think **saves the most energy.**

Decreasing one incandescent light bulb's use from 4 hours to 3 hours	Using one LED light bulb for 4 hours **instead of** an incandescent light bulb
Reducing the use of a window air conditioning unit from 5 hours to 3 hours	Keeping a ceiling fan on for 5 hours **instead of** using a window air conditioning unit
Reducing the use of a dehumidifier from 10 hours to 5 hours	Purchasing a 20% more efficient dehumidifier and using it for 10 hours **instead of** using a standard dehumidifier
Decreasing the use of one CFL bulb from 2 hours to 1 hour	Using one LED bulb for 2 hours **instead of** a CFL bulb
Decreasing the use of one CFL bulb from 10 hours to 1 hour	Using one LED bulb for 10 hours **instead of** a CFL bulb
Reducing the use of a projector to watch movies from 10 hours to 9 hours a week	Using a smartphone for 10 hours a week to watch movies **instead of** a projector
Decreasing the use of a central air conditioning unit from 6 hours to 5 hours	Using a ceiling fan for 6 hours **instead of** a central air conditioning unit
Reducing the use of a space heater from 5 hours to 4 hours	Using an electric blanket for 5 hours **instead of** a space heater
Reducing the use of a desktop computer to play music from 10 hours to 5 hours	Using a stereo to play music for 10 hours **instead of** a desktop computer

{Page Break}

https://www.szattari.com/s/SimpleInterventions_Data.xlsx

Pairwise Section			
PW_1_	For each question below, read the two options presented and choose the option that **saves the most energy**. (a) Decreasing one incandescent light bulb's use from 4 hours to 3 hours (b) Using one LED light bulb for 4 hours instead of an incandescent light bulb	1 = a; 2 = b; correct ans: 2	1 = 100; 2 = 340; multiplier ~ 3.4
PW_2_	(a) Reducing the use of a window air conditioning unit from 5 hours to 4 hours (b) Keeping a ceiling fan on for 5 hours instead of using a window air conditioning unit	1 = a; 2 = b; correct ans: 2	1 = 1157 2 = 5440 multiplier ~ 4.7
PW_3_	(a) Reducing the use of a dehumidifier from 10 hours to 5 hours (b) Purchasing a 20% more efficient dehumidifier and using it for 10 hours instead of using a standard dehumidifier	1 = a; 2 = b; correct ans: 1	1 = 3667.5 2 = 1467 multiplier ~ 2.5
PW_4_	(a) Decreasing the use of one CFL bulb from 2 hours to 1 hour (b) Using one LED bulb for 2 hours instead of a CFL bulb	1 = a; 2 = b; correct ans: 1	1 = 23 2 = 16 multiplier ~ 1.44
PW_5_	(a) Decreasing the use of one CFL bulb from 10 hours to 1 hour (b) Using one LED bulb for 10 hours instead of a CFL bulb	1 = a; 2 = b; correct ans: 1	1 = 207 2 = 80 multiplier ~ 2.59
PW_6_	(a) Reducing the use of a projector to watch movies from 10 hours to 9 hours a week (b) Using a smartphone for 10 hours a week to watch movies instead of a projector	1 = a; 2 = b; correct ans: 2	1 = 198 2 = 1947.5 multiplier ~ 9.85
PW_7_	(a) Decreasing the use of a central air conditioning unit from 6 hours to 5 hours (b) Using a ceiling fan for 6 hours instead of a central air conditioning unit	1 = a; 2 = b; correct ans: 2	1 = 3796.6 2 = 22029.6 multiplier ~ 5.8
PW_8_	(a) Reducing the use of a space heater from 5 hours to 4 hours (b)Using an electric blanket for 5 hours instead of a space heater	1 = a; 2 = b; correct ans: 2	1 = 1290 2 = 5463 multiplier ~ 4.23
PW_9_	(a) Reducing the use of a desktop computer to play music from 10 hours to 5 hours (b)Using a stereo to play music for 10 hours instead of a desktop computer	1 = a; 2 = b; correct ans: 1	1 = 690.65 2 = 131.3 multiplier ~ 5.26
Personal Energy Use and Sticky			
CorE	In general, do you believe that you can save more energy by: (a) Reducing how often you use an appliance (b) Replacing an appliance with a more efficient model	0 = a; 1 = b;	
TOTL_Freq	When you are the last person to leave a room with the lights turned on, how often do you turn off the lights?	1 = Hardly ever 2 = Not very often 3 = Often 4 = Always	
Eff_Bulbs	What percent of the light bulbs at your current residence are energy-efficient, such as CFL or LED bulbs?	Open-ended	
Sticky	The most frequent response to "What is the single most effective thing you could do to save energy?" has been turning off the lights. While turning off the lights does save some energy, many other actions have the potential to save a lot more energy. With this in mind, why do you think people continue to list "turning off the lights" as the most effective energy saving action they could do?	Open-ended	
Climate Change Attitude Questions			

AutoSave Home Insert Draw Page Layout Formulas Data Review View Automate TOTL+Data General Data*

I54 1

	A	B	C	D	E	F	G
1	ID	Time	Currently_do	Could_do	Friend	Friend_Explain	C_Easy
2	1	196	sleep	die?	1	I just chose	1
3	2	243	keep heat low	bike to work	1	better over all	1
4	3	214	i meditate	yoga	0	i just picked off intuition	3
5	4	323	turn lights off	turn lights off more	1	It seems it will be more effective.	2
6	5	310	walk to the store	walk to work	0	using no energy is best	1
7	6	348	keep all lights off when not using the	use less electronics	0	I thought it was the best one for me	2
8	7	320	do not use AC or the heater at all	I could turn the lights off when I am not using it	1	just thinking of the overall lifetime of the lights and how long they could last and	2
9	8	369	dont drive	work from home	0	Not using any electric save more energy	1
10	9	282	Getting plenty of sleep	Having less stress	1	Using these bulbs will help save energy instead of turning it all off. That isn't feasib	4
11	10	276	i CURRENTLY TURN MY ac OFF DURIN	I COULD BE RIDING A BIKE TO WORK INSTEAD OF A CAR	0	I WENT BY WHAT I ASSUMED WAS THE CORRECT ANSWER	5
12	11	391	turn off lights and AC when I leave	cook less	1	Assuming he doesn't change his habits, changing the bulbs will reduce energy	1
13	12	357	I rarely use ac or heat	Replace windows and doors	0	it seems more effective in the long run.	1
14	13	386	I try to reduce household energy con	I can use public transportation/bike to work and school.	0	I guessed that this would be more effective	1
15	14	318	Shut lights off when I leave a room.	Turning off water when I'm not using it.	0	Turning off lights saves more energy in the long run.	2
16	15	224	led build	turn off the light us less water	1	it's easier to replace the bulds	2
17	16	304	I turn off the lights when I leave a roo	I could buy an electric car.	1	Most people forget to turn off the lights so if they used more efficient bulbs it wou	1
18	17	381	I pack lunch and get my clothes out t	I could be eating a better breakfast to get my energy going in the mo	0	Leaving the lights on, even more efficient bulbs, uses energy. I feel like most peopl	1
19	18	388	I changed all my light bulbs to energy	I could take public transportation more.	1	I think people who always have their lights on could save energy by switching bul	1
20	19	401	use m turk at work for extra pay	getting more sleep	1	in the long term changing the bulbs would get you more savings - for the first que	1
21	20	391	I try to prioritize what needs to be dc	I could go to bed earlier to get more sleep.	1	I work for a lighting company so I know that switching to LED lights will generate	2
22	21	418	turn off the lights when I leave	showering less	1	I thought of how long the lights would be on when you leave.	1
23	22	350	turn lights off	use my ac less	1	because im sure he has a lot of bulbs in his house and swapping them out will save	2
24	23	353	meditate	avoid negative people	0	logic	1
25	24	314	I make sure that I am getting enough	I could be driving to less places	1	I chose my previous answer based off of the efficiency of the bulb	2
26	25	380	I turn off my lights when i am not in a	Putting time limited on certain alliance and unpluging them	1	It seems like It ill be easiest thing to keep up. I and others can just install this and i	1
27	26	453	must job	money	0	very good	2

28	27	398	walk whenever possible	recycle more	0	I think though energy efficient bulbs will certainly help, turning off the light altog	5
29	28	375	turn down the heat	take colder showers	0	not using light at all saves a lot of energy	1
30	29	304	turn off all the lights when not in use	switch to all energy efficient appliances	1	she might already turn off the lights when not in use, this will save energy even wh	2
31	30	411	I turn off the lights.	I could have a better thermostat.	1	This is a simple one time step and he doesn't have to change any.	1
32	31	501	I use solar panels at me house	I could by a electric car.	1	I know that my friends aren't home that much so they don't have or leave the ligh	1
33	32	403	Turn off the light when I don't use it	Carpool	1	It think using that lightbulb will save more energy in long run	2
34	33	476	turn off the air conditioner	to have a system for saving	0	it is the healthiest option	1
35	34	296	Turn off the lights when not in the ro	Turn off the computers when not actively using them.	1	Once you change the bulbs you can't forget to turn them off.	2
36	35	497	Keep my house cooler.	Making sure everything that is not in use is turned off.	0	If it is only over a period of one month, it's cheaper to turn off lights. LED bulbs wo	1

Attari, S. Z., Krantz, D. H., & Weber, E. U. (2016). Energy conservation goals: What people adopt, what they recommend, and why. *Judgment and Decision Making*, *11*(4), 342–351. https://doi.org/10.1017/S1930297500003776
https://www.szattari.com/publications

Energy conservation goals: What people adopt, what they recommend, and why

Shahzeen Z. Attari* David H. Krantz† Elke U. Weber‡

Abstract

Failures to reduce greenhouse gas emissions by adopting policies, technologies, and lifestyle changes have led the world to the brink of crisis, or likely beyond. Here we use Internet surveys to attempt to understand these failures by studying factors that affect the adoption of personal energy conservation behaviors and also endorsement of energy conservation goals proposed for others. We demonstrate an asymmetry between goals for self and others ("I'll do the easy thing, you do the hard thing"), but we show that this asymmetry is partly produced by actor/observer differences: people know what they do already (and generally do not propose those actions as personal goals) and also know their own situational constraints that are barriers to action. We also show, however, that endorsement of conservation goals decreases steeply as a function of perceived difficulty; this suggests a role for motivated cognition as a barrier to conservation: difficult things are perceived as less applicable to one's situation.

Keywords: energy conservation, actor/observer bias, motivated reasoning

1 Introduction

As part of a study of perceptions of energy use and savings, Attari, DeKay, Davidson and Bruine de Bruin (2010) asked subjects to name "the most effective thing that you could do to conserve energy in your life". Many answers (about 20%) involved variations on "turning off lights", but others suggested more major changes in life style (e.g., "drive less") or increased efficiency of cars or appliances. In the present studies we explore some factors that correlate with choice of these different answers. In particular, we ask how answers for oneself differ from answers proposed for others (the most effective thing that *Americans* can do). These explorations are important in order to understand both adoption of individual change goals and endorsement of energy conservation policies that would apply to all Americans.

We expected people to favor "low hanging fruit" both for themselves and others: changes that are highly effective but not too difficult. Thus, two obvious factors that we expected to correlate with behavioral change goals (for self) and policy goals (changes that others should make) are the *perceived effectiveness* and the *perceived difficulty* of the changes. In addition, we expected people to omit goals not applicable to their lives: for example, urban dwellers who rely mostly on public transportation will not propose to conserve energy by driving less or buying energy-efficient cars (even though they may suggest these changes for others). Finally, there is a conversational rule (Grice, Cole & Morgan, 1975) that may be important: something that one does already is not usually put forward as a goal. Someone who is already assiduous about turning off lights is thus less likely to endorse that as a behavioral goal for self.

These obvious factors suggest reasons why goals for self and others might differ. Perceived effectiveness and difficulty should play a role in both; but perception of appli-

Table 1: Percentage of open-ended endorsements provided in Study 1 and Study 2 for the single most effective behavior for self and Americans.

	Study 1 (N = 717)		Study 2 (N = 685)	
Categories	Self	Americans	Self	Americans
Turn off lights	19.5	13.0	13.6	10.2
Drive less	19.3	31.8	19.3	31.8
Turn off appliances	10.9	7.8	12.6	10.7
Change setting on the thermostat	9.1	4.6	10.7	5.7
Sleep/relax more	7.3	4.6	1.8	1.3
Use appliances less	5.4	4.6	8.3	4.7
Unplug appliances	5.0	2.8	7.0	4.5
Conserve water/energy	4.6	4.5	4.2	1.5
Use energy efficient bulbs	2.8	3.6	2.8	3.6
Consume less	2.7	4.0	0.9	2.2
Other (each only mentioned once)	2.4	1.8	4.5	3.2
Use efficient cars/hybrids	2.2	2.2	2.3	6.7
Use efficient appliances	1.8	2.9	3.9	3.1
Change my lifestyle	1.8	2.5	1.3	0.9
Buy green energy	1.3	3.2	1.6	3.4
Buy green products	1.1	1.0	0.3	0.0
Eat green	1.0	1.0	0.6	0.3
Recycle	0.7	1.4	0.9	1.5
Insulate my home/weatherize	0.4	0.4	1.3	1.5
There is no way/I don't know	0.4	0.4	0.1	0.0
Awareness/education; more attention	0.1	1.4	1.8	2.8
Phase out inefficient technologies	0.1	0.4	0.0	0.6

behaviors they perceive as difficult, but might do this less in recommendations for others.

In this article we present a very brief Study 1, showing an asymmetry between goals for self and for others, and a more complex Study 2, which replicates the asymmetry and explores the factors that affect adoption of conservation goals for self and conservation policies for others.

> In your opinion, what is the single most effective thing that **Americans** could do to use less energy in their life?

Coding. The open-ended responses to both questions were sorted by two independent coders into 22 categories (see row labels in Table 1). These categories were devised by examining an initial subset of 40 surveys. All the survey responses were then coded independently by the two

Do it already/Difficulty. Next, participants answered questions about how easy or difficult they found each of the behaviors. As part of the probe of perceived difficulty, we asked respondents whether they claimed to do the action in question already. “Do it already” was placed as the extreme left end of a response scale, with the rest of the scale offering six levels from “Extremely easy” to “Extremely hard”. The probe was:

> Please indicate how easy or hard it would be for you to make each of the following changes. Please consider all aspects of the changes, including the physical or mental effort required, the time or hassle involved, and any relevant monetary costs. If you already engage in the activity please check “do it already” (far left).

This design was motivated by two considerations: first, “do it already” provides a desired self-report of actions taken; second, we felt that difficulty judgments might have a different basis for actions experienced versus imagined. We opted to obtain only the latter, from those who did not claim to do it already, and to accept the consequent limitations on using the difficulty scale in data analysis. In this design we are able correlate respondents’ self-reported energy conservation actions (whether they do the action already) with their perceptions of effectiveness and applicability for those same actions, and with other individual-level variables, but not with their individual perceptions of difficulty.

Effectiveness. Similarly, participants were asked to rate on a four-point scale how effective they found each behavior: Hardly effective at all, Somewhat effective, Substantially effective, Extremely effective. The question stated:

> Please indicate how effective or ineffective each of the following behaviors is in terms of decreasing an individual’s energy use.

Applicability. Participants then were asked how applicable each behavior was to their lives with three response options: Very applicable, Somewhat applicable, and Not at all applicable. The question stated:

> Please indicate how applicable or not applicable each of the following behaviors is to your life. In considering how applicable each behavior is, consider whether the behavior is relevant to your life.

Other survey items. Subsequent questions included the New Ecological Paradigm (NEP) scale, a 15-item instrument for assessing pro-environmental attitudes (Dunlap,

the pro-environmental direction and averaged them to yield an overall NEP score for each participant. Participants also rated four statements regarding personal efficacy and belief in climate change (e.g., “I believe that I need to change my lifestyle to address global warming and climate change”), which we used to calculate an overall *climate-change attitude* score. Next participants completed Schwartz et al.’s (1997) *numeracy* assessment, which consists of three open-ended questions. Demographic questions concluded the survey. The entire survey is available in the supplement.

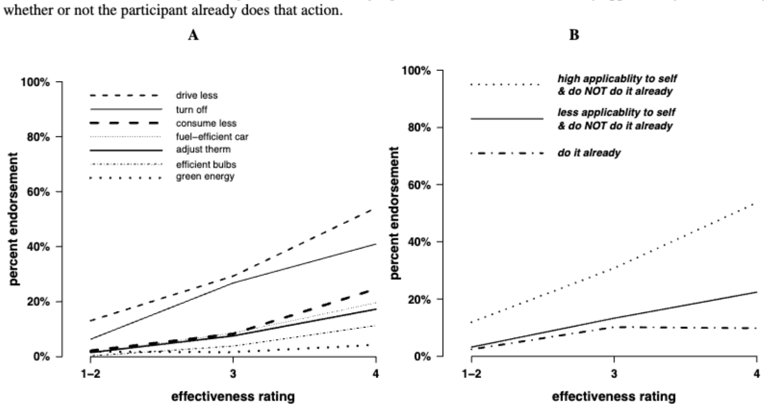
3.1 Results for Study 2: Overview

We begin with this overview of all the results, then follow with detailed analyses in the same order as the overview. We first follow up Study 1 by analyzing the responses to the two open-ended questions (self and Americans); we add to this similar analyses for the endorsements for the closed-ended list of actions. This set of analyses shows that the asymmetries found in Study 1 are replicated, both for open-ended responses and endorsements for the closed-ended list. It also emerges that order of asking about self versus Americans has at most small effects.

Next we relate endorsements of the closed-ended list of actions to ratings of perceived effectiveness, to ratings of applicability of the actions, and to whether or not the actions have already been adopted. As predicted, endorsement of an action for self correlates with all three of these variables: people are more likely to endorse actions that they view as effective and as applicable to their lives, and are unlikely to endorse as goals actions that they do already. Endorsement of an action for Americans, on the other hand, depends mainly on perceived effectiveness of the action. This difference between factors underlying endorsement shows the importance of probing assumptions in formulating questionnaire items. Without applicability and do it already questions, we would misunderstand people’s endorsements for self.

These first two segments of results do not take account of the difficulty of the actions on the closed-ended list. Recall that difficulty was rated only for those actions not reported as “do it already”. Thus, perceived difficulty cannot easily be included in linear models for endorsement of an action. We can, however, relate both the perceived effectiveness of an action and the probability of endorsing that action to *average difficulty*, a consensus measure based on the ratings of those who do not report “do it already”. We find that perceived effectiveness increases with this difficulty average, but the slope is shallow. In contrast, perceived applicability to one’s life and reports of “do it already” decreases sharply with the consensus difficulty.

Figure 1: **(A)** Endorsement of actions for other Americans related to judged effectiveness of the actions; **(B)** Endorsement for self of ’drive less’ and ’adjust thermostat’ related to judged effectiveness of those actions and to other factors. The endorsement for self is similar for these two actions and thus represents both well. Judged effectiveness operates similarly for the other actions (omitted). The figure also shows how judged effectiveness is moderated by applicability to self and by whether or not the participant already does that action.



average only two actions, with rather similar regression coefficients, than to average across heterogeneous regressions or to present a confusing display with separate curves for the 7 actions. The simpler display allows separate curves as a function of perceived applicability and “do it already”.

Table 5: Logistic regression coefficients (± *1 estimated standard error*).

Endorsement for Self				
Action	Intercept	Effective	Applicable	Do it already
Drive less	−3.74 ±0.56	+0.63 ±0.16	+1.43 ±0.22	−1.96 ±0.29

Turn off	−1.87 ±0.38	+0.75 ±0.12	+0.34 ±0.27	−1.93 ±0.19	
Consume less	−4.77 ±0.67	+0.69 ±0.19	+1.08 ±0.28	−1.58 ±0.42	
Fuel-efficient car	−5.44 ±0.77	+0.90 ±0.22	+0.42 ±0.38	−1.04 ±0.66	
Adjust thermostat	−4.82 ±0.57	+0.93 ±0.17	+0.93 ±0.29	−1.44 ±0.26	
Efficient bulbs	−5.62 ±0.85	+1.01 ±0.27	+0.93 ±0.52	−0.26 ±0.48	
Green electricity	−5.44 ±1.05	+0.33 ±0.35	+2.06 ±0.60	−0.84 ±1.10	
Endorsement for Americans					
Action	Intercept	Effective	Applicable	Do it already	Observed percent
Drive less	−3.79 ±0.45	+0.96 ±0.13	+0.02 ±0.18	+0.17 ±0.19	38.7%
Turn off	−4.21 ±0.49	+0.99 ±0.13	+0.27 ±0.33	−0.43 ±0.19	24.1%
Consume less	−6.41 ±0.77	+1.24 ±0.21	+0.59 ±0.26	−0.42 ±0.30	13.9%
Fuel-efficient car	−5.95 ±0.73	+1.13 ±0.21	+0.28 ±0.34	−0.15 ±0.46	9.6%
Adjust thermostat	−6.26 ±0.79	+1.06 ±0.22	+0.63 ±0.40	−0.06 ±0.30	8.2%
Efficient bulbs	−8.46 ±1.27	+1.46 ±0.33	+1.07 ±0.80	−0.48 ±0.48	3.4%
Green electricity	−4.74 ±0.91	+0.28 ±0.31	+0.51 ±0.69	+0.70 ±0.88	2.2%

We assessed the association of ratings of *do it already*, *perceived effectiveness*, and *perceived applicability* with endorsement of each of the 7 alternatives in the closed-ended list by separate logistic regressions (even though the dependent variables are not independent of each other). For *perceived applicability* the two lower levels of the scale, *somewhat* and *not at all applicable*, were combined, as they did not lead to distinct predictions. Thus *perceived applicability* was converted to a dichotomous variable for the regressions.[3]

Table 5 shows the coefficients for logistic regressions for each of the 7 actions in the closed-ended list.

For both self and Americans, the logistic regression coefficients for *perceived effectiveness* were statistically significant for all but one action. The exception was *green energy*, the action least endorsed.

The coefficients for *perceived applicability* for self were all positive; this factor was statistically significant and substantial for endorsement of *drive less, consume less, adjust thermostat,* and *green energy*. Note that *turn off* is judged highly applicable by 88% of respondents; as a result, *per-*

With respect to actions for self, the coefficients for *do it Already* are negative for all 7 actions, though statistically significant only for *drive less*, *turn off*, *consume less*, and *adjust thermostat*. Overall, 75% of respondents endorsed an action for themselves that they did not do already. A conversational norm – *endorse for yourself an action that you do not do already* – contributes to the asymmetry between self and Americans.

The results for self suggest that respondents know whether they already do a particular action and also readily think of reasons why an action is not personally applicable to their lives.

3.4 Study 2: Difficulty ratings and perceived effectiveness or applicability

It seems natural that perception of both effectiveness and applicability would relate to the difficulty of actions. Something that seems difficult might be judged more effective by some respondents, just for that reason, but might also

3.4 Study 2: Difficulty ratings and perceived effectiveness or applicability

It seems natural that perception of both effectiveness and applicability would relate to the difficulty of actions. Something that seems difficult might be judged more effective by some respondents, just for that reason, but might also
be judged inapplicable for that same reason (a form of motivated cognition). Since difficulty was judged on an easy/hard scale only by respondents who did not report "do it already", we examine these hypotheses by using the consensus rating of difficulty, the average rating by those who do not self-report doing the action. These average ratings

Figure 2: Perceived effectiveness related to mean difficulty of actions. The vertical axis indicates the percentage of respondents who gave each of the seven (labeled) actions the highest effectiveness rating (shown by open triangles) and also the two highest effectiveness ratings (shown by closed circles). The horizontal axis shows the mean difficulty rating of the seven actions based on the subset of participants who do not report "do it already".

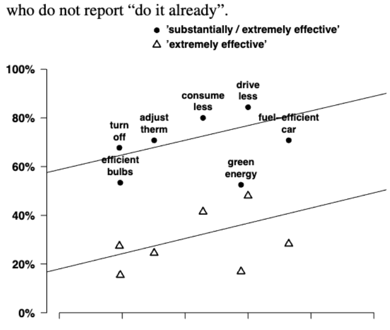
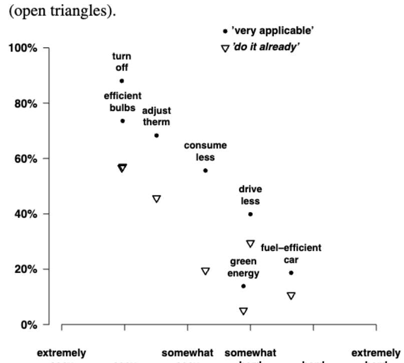
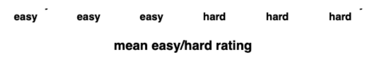


Figure 3: Perceived applicability and self-report of doing an action already related to mean difficulty of actions. Consensus (mean) difficulty judgments for each of the 7 behaviors (from those not doing it) is on the abscissa; the ordinates are percentages: those who find that action "very applicable" (black filled circles) and those reporting "do it already" (open triangles).





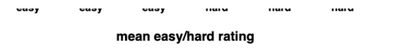
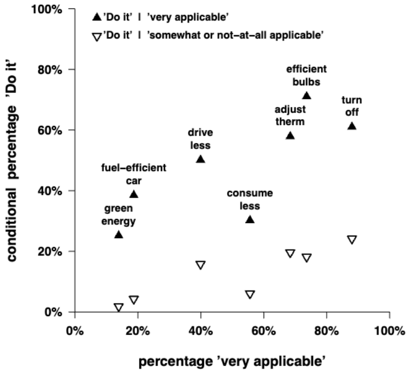


Figure 4: Conditional relationships between perceived applicability and self-reported action.



3.5 Study 2: Self-reports of "do it already"

The percentage of respondents who reported "do it already" varied across the seven actions on the closed-ended list, from 57% (for *turn off* and also for *efficient bulbs*) down to 5% (for *green energy*). These reports are of course positively correlated: fully 14% of the sample report doing none of these actions (only 5% would be expected, under independence), while 22% report doing four or more out of seven. The total count of actions for which respondents re-

increases.

4 Discussion

When asked about the single most effective action they themselves can do to conserve energy, people tend to list easier and less effective behaviors such as turning off the light. In fact, as a choice for self, "turning off the light" has been a modal response documented in the 1980s (Kempton, Harris, Keith & Wehl, 1985). When asked about the single most effective action that Americans can do to conserve energy, people tend to list harder but more effective behaviors such as driving less. This finding holds when the order of the questions is reversed and is confirmed by respondents' own ratings of effectiveness. This finding may have a rather complicated theoretical basis and it suggests approaches to promotion of conservation by individual efforts and by policy changes.

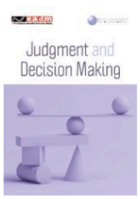
One possible explanation for the asymmetry is actor/observer bias: people understand the situational factors that constrain their own behavior much better than they understand similar constraints for others (Jones & Nisbett, 1971). In other words, people believe that Americans should do harder and more effective actions, even though they themselves cannot engage in these effective actions due to limitations posed by situational context. The asymmetry may reflect genuine differences between actions feasible for the individual, given his or her situation, from those perceived as feasible for the average American. Thus, the asymmetry may not be motivated by selfishness or by a social-dilemma calculus, but may be dictated by situational

a test of null hypothesis, t = 1.96/0.45 ≈ 4.36 (in essence, a McNemar test of symmetry).

[2] The average curves look similar for all 7 actions but it seemed better to average only two actions, with rather similar regression coefficients, than to average across heterogeneous regressions or to present a confusing display with separate curves for the 7 actions. The simpler display allows separate curves as a function of perceived applicability and "do it already".

[3] Perceived effectiveness and perceived applicability are correlated around –0.2 for each action. This negative correlation somewhat resembles the results from Alhakami & Slovic (1994), who found an inverse relationship between judgments of risks and benefits.

https://www-cambridge-org.proxyiub.uits.iu.edu/core/journals/judgment-and-decision-making/article/energy-conservation-goals-what-people-adopt-what-they-recommend-and-why/47B66AC4270DDBEFF8ABCA3C15F86BC8#supplementary-materials



Judgment and Decision Making

Article contents

Energy conservation goals: What people adopt, what they recommend, and why

Published online by Cambridge University Press: **01 January 2023**

Shahzeen Z. Attari, David H. Krantz and Elke U. Weber

Show author details

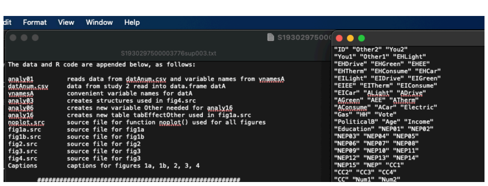
Article | Figures | **Supplementary materials** | Metrics

Attari et al. supplementary material
Attari et al. supplementary material 1
File 124 KB

Attari et al. supplementary material
Attari et al. supplementary material 2
File 764 Bytes

Attari et al. supplementary material
Attari et al. supplementary material 3
File 9.4 KB

Attari et al. supplementary material
Attari et al. supplementary material 4
File 127.7 KB




```
The data and R code are appended below, as follows:

analy01         reads data from datAnum.csv and variable names from vnamesA
datAnum.csv     data from study 2 read into data.frame datA
vnamesA         convenient variable names for datA
analy03         creates structures used in fig4.src
analy06         creates new variable Other needed for analy16
analy16         creates new table tabEffectOther used in fig1a.src
noplot.src      source file for function noplot() used for all figures
fig1a.src       source file for fig1a
fig1b.src       source file for fig1b
fig2.src        source file for fig2
fig3.src        source file for fig3
fig4.src        source file for fig3
Captions        captions for figures 1a, 1b, 2, 3, 4

     ##################################################
```

```
"ID" "Other2" "You2"
"You1" "Other1" "EHLight"
"EHDrive" "EHGreen" "EHEE"
"EHTherm" "EHConsume" "EHCar"
"EILight" "EIDrive" "EIGreen"
"EIEE" "EITherm" "EIConsume"
"EICar" "ALight" "ADrive"
"AGreen" "AEE" "ATherm"
"AConsume" "ACar" "Electric"
"Gas" "HH" "Vote"
"PoliticalB" "Age" "Income"
"Education" "NEP01" "NEP02"
"NEP03" "NEP04" "NEP05"
"NEP06" "NEP07" "NEP08"
"NEP09" "NEP10" "NEP11"
"NEP12" "NEP13" "NEP14"
"NEP15" "NEP" "CC1"
"CC2" "CC3" "CC4"
"CC" "Num1" "Num2"
```

```
analy01
#### Reading numeric data and simplifying names
#
datA <- read.table("datAnum.csv",head=T)
names(datA) <- scan("vnamesA", "")  ## after editing!
attach(datA)
Group <- rep("Other1st", 685)
Group[is.na(Other2)] <- "You1st"

        ######################################################
analy03
attach(datA)
doLight <- EHLight==1
doDrive <- EHDrive==1
doGreen <- EHGreen==1
doEffic <- EHEE==1
doTherm <- EHTherm==1
doConsume <- EHConsume==1
doCar <- EHCar==1
AdoGrp <- list(
   AdoLightGrp = table(doLight, ALight, Group),
   AdoDriveGrp = table(doDrive, ADrive, Group),
   AdoGreenGrp = table(doGreen, AGreen, Group),
   AdoEEGrp = table(doEffic, AEE, Group),
   AdoThermGrp = table(doTherm, ATherm, Group),
   AdoConsumeGrp = table(doConsume, AConsume, Group),
   AdoCarGrp = table(doCar, ACar, Group))
AdoGrpTest <- lapply(AdoGrp,
       function(w) loglin(w, list(1:2, 3), fit=T, print=F))
AdoGrp.lrt <- sapply(AdoGrpTest, function(w) w$lrt)
AdoGrp.lrt
Ado<- list(
   AdoLight= table(doLight, ALight),
   AdoDrive= table(doDrive, ADrive),
   AdoGreen= table(doGreen, AGreen),
   AdoEE= table(doEffic, AEE),
   AdoTherm= table(doTherm, ATherm),
   AdoConsume= table(doConsume, AConsume),
   AdoCar= table(doCar, ACar))
AdoTest <- lapply(Ado, function(w) loglin(w, 1:2, print=F))
Ado.lrt <- sapply(AdoTest, function(w) w$lrt)
Ado.lrt
AdoP <- lapply(Ado, function(w) round(d=3, w/sum(w)))
AdoP


        ######################################################
analy06
attach(datA)
##########################
You <- rep(0, 685)
You[!is.na(You1)] <- You1[!is.na(You1)]
You[!is.na(You2)] <- You2[!is.na(You2)]
##########################
Other <- rep(0, 685)
Other[!is.na(Other1)] <- Other1[!is.na(Other1)]
Other[!is.na(Other2)] <- Other2[!is.na(Other2)]
```

```
"Num3" "Num" "EnergyTried"
"EnergyCould" "Rent" "Dem"
"Rep" "Ind" "NoVote"
"CouldntVote" "Sex" "YouLight"
"YouDrive" "YouGreen" "YouEE"
"YouTherm" "YouConsume" "YouCar"
"OtherLight" "OtherDrive" "OtherGreen"
"OtherEE" "OtherTherm" "OtherConsume"
"OtherCar" "Condition"
```

Energy and Behavior Survey: SELF-OTHER ORDER

Dear Participant:

Your involvement in this study will help us understand behaviors related to energy consumption. Thank you for your time and help with this effort.

Please note that participation is voluntary. The survey is anonymous, and no one will know what answers you give. For this reason, please do not type your name or anyone else's name anywhere in the survey. The survey is relatively brief and should not take any more than 10 minutes to complete.

Thank you again for participating in this study. The asterisks denote questions for which you must provide answers for before going to the next screen. If you feel uncomfortable in answering any question, you can exit the survey. On completing the survey, you will be paid via $3 MTurk within 72 hours. There is a limit of one gift certificate per person.

If you have any questions, please do not hesitate to send me an email at: sattari@indiana.edu.

Sincerely,
Shahzeen Attari

[A progress bar is shown at the bottom of every page.] *<page break>*

1. OPEN-ENDED SELF QUESTION

In your opinion, what is the single most effective thing that ***you*** could do to use less energy in your life?

____

<page break>

2. OPEN-ENDED OTHER QUESTION

In your opinion, what is the most effective thing that ***Americans*** could do to use less energy in their life?

____

<page break>

3. CLOSED-ENDED SELF QUESTION

Which of the following behaviors is the single most effective behavior that ***you*** could do to use less energy in your life? *(Please check one behavior)*

Schille-Hudson, E. B., Margehtis, T., Miniard, D., Landy, D., & Attari, S. Z. (2019). Big, hot, or bright? Integrating cues to perceive home energy use. *Proceedings of the 41st Cognitive Science Society*.

on these proximal cues.

Participants' estimates of appliances' energy use were driven almost entirely by how large they judged the appliance to be (b = 0.10 ± 0.01 SEM, p<.001). Most variance in estimates is accounted for by differences in *size*. By contrast, people's judgments of how much the appliance changed the temperature and of how "electronic" an appliance was also had much smaller relations to their energy estimates (b = 0.04 ± 0.01 SEM, p<.001, b = 0.05 ± 0.01 SEM, p<.001). Critically, we found no relation between judgments of how often an appliance is used and estimates of how much energy it uses — despite past work that has argued that frequency-of-use is used as a 'replacement heuristic' for energy estimation (Schley & DeKay, 2015). Note that people's estimates of energy use were explained primarily by judgments of the appliance's size rather than by how much the appliance changed the temperature, even though heat is a more reliable cue to energy use, because heating and cooling use a lot of energy.

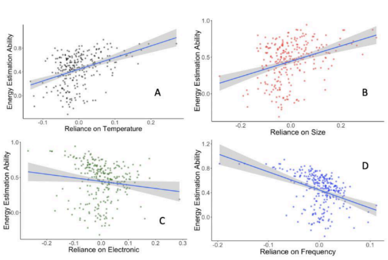
Individual differences in the use of proximal cues to estimate home energy use

We next investigated individual differences in the features that were associated with energy estimates — that is, we asked whether some people relied more on some proximal cues (e.g., size) than on others (e.g., temperature change).

	Size	Electronic	Frequency **of use**	Temp**erature** Change
Size	1.00	0.183	0.066	0.215
Elect.		1.00	0.103	-0.131
Freq.			1.00	0.023
Temp.				1.00

Table 1: Correlation matrix of key features

Figure 2: Energy estimation ability as predicted by reliance on select features



who relied more on electronic-ness and frequency-of-use were overall worse at estimating home energy use (b = -

incandescent lightbulbs, Compact Fluorescent Light bulb, and LED bulb) group together because people rated those were overall worse at estimating home energy use (b = -0.51 ± 0.24 SEM, p<.05, b = -2.96 ± 0.43 SEM, p<.001). We also ran a correlation on the participants' reliance on each of these four features (Table 1). We found reliance on frequency of use and electronic-ness to be positively correlated, while frequency of use and temperature change were negatively correlated.

Characterizing the complex structure of the full appliance space

Finally, we combined ratings of all thirteen features (e.g., size, brightness, movement, etc.) to characterize lay perception of home appliances. To do so, we used multi-dimensional scaling (MDS). This technique takes the similarity between paired appliances and uses that to generate a reduced dimensional representation that captures how similar or different appliances are to each other. This approach gets at the rich structure that exists in how people perceive appliances as varying along multiple dimensions, many of which covary with each other. This approach is also necessary, because when dimensions are treated as independent, classic approaches like multiple

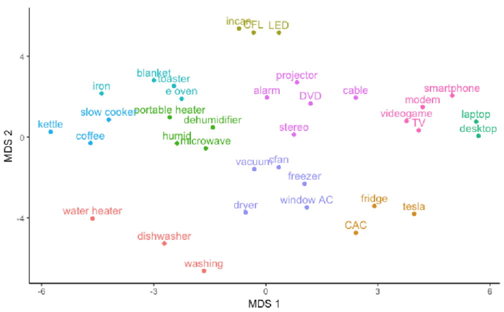
LED bulb) group together because people rated those appliances very similarly.

While this MDS solution can characterize people's mental representations of appliances, it is blind to people's estimates of the appliances' energy use. However, when we regressed the MDS dimensions onto estimation ability, we found both MDS axes were related significantly to energy estimates increase (dimension 1: b = 146.88 ± 67.5 SEM, p<.05; dimension 2: b = -254.68 ± 104.0 SEM, p<.05). This was true despite the fact that these MDS dimensions combine multiple experiential features in complex, non-linear ways. Thus, lay people have structured perceptions of appliances, and these perceptions seem to relate systematically to their perceptions — and misperceptions — of their energy use. Future work should try to leverage this to improve energy decisions and behaviors.

Discussion

We began by asking how it is that people are able to estimate the energy used by appliances, when that energy use is often hidden. We found that estimates of appliances' size accounted for most of the variance in people's energy estimates. People

Figure 3: Two-dimensional MDS solution for home appliance space



heuristic' might indicate that people tend to use bigger appliances more often. Interestingly, people relied more on size than heat, despite heat being a better indication of energy use. Heating (and cooling) both take a lot of energy but are perhaps not as obvious to people because the energy used to heat (and cool) are often used to achieve homeostasis. Your heating bill is high in the winter because so much energy has to be exerted to maintain your home at a constant temperature.

When we examined individual differences in the reliance on these cues, we found that the degree to which people relied on certain features predicted how good their energy estimates were. People who relied more on temperature change had better energy estimates than people who relied more on size, or any of the other theory-driven features used in our model. The more participants relied on how "electronic" an appliance was or on

Using multi-dimensional scaling, we also sought to characterize the public's mental representation of home appliances. This bottom-up approach found significant structure in people's perceptions of appliances; moreover, this two-dimensional representation was related systematically to people's energy estimates. In Fig. 3, the upper-left quadrant of the graph seems to include all the appliances that heat water, while the lower-left quadrant includes the appliances that heat without water. This suggests that this two-dimensional MDS solution has picked out *heat* as a notable component of one of its major axes. The appliances near the top of Fig. 3 are quite small and increase in size as you go down the MDS 2 axis, suggesting that this MDS solution has picked out size as a major component of its other axis. It is quite notable that even just a two-dimensional solution has, in a bottom-up way, picked out the two most useful and frequently used replacement heuristics. The clustering as shown in Fig. 3, also

Appendix: Features

1. How **big** is each appliance?
2. How **long** is each appliance typically used?
3. How much **light** does each appliance produce?
4. How much does each appliance **heat** itself or its environment?
5. How **loud** is each appliance?
6. How much **water** does each appliance use?
7. How much does each appliance **cool** itself or its environment?
8. How big is the **motor** of each appliance?
9. How much does each appliance **heat water**?
10. How complex is the **software** each appliance runs?
11. How **electronic** is each appliance?
12. How **mechanical** is each appliance?
13. How much does each appliance **move** itself or its environment?
14. How **frequently** do you use each appliance?

Chisik, Y. (2011). An Image of Electricity: Towards an Understanding of How People Perceive Electricity. In P. Campos, N. Graham, J. Jorge, N. Nunes, P. Palanque, & M. Winckler (Eds.), *Human-Computer Interaction – INTERACT 2011* (Vol. 6949, pp. 100–117). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-23768-3_9 https://inria.hal.science/hal-01596997/file/978-3-642-23768-3_9_Chapter.pdf

An Image of Electricity: Towards an Understanding of How People Perceive Electricity

Yoram Chisik

Madeira Interactive Technologies Institute (M-ITI) - University of Madeira
Campus da Penteada, 9020-105 Funchal, Portugal
ychisik@m-iti.org

Abstract. Although an enormous amount of research effort has been devoted to understanding people's energy consumption habits, visualizing their consumption and finding ways of motivating them towards more sustainable behaviours we are still in the dark with regards to people's basic perception of electricity, their concept of what electricity is and their notion of the consumption

rates of various electrical devices. In this study we have employed a sketching methodology to elicit people's basic mental image of what electricity is, how they conceive of the electrical infrastructure in their home and which devices they think represent the largest drain on their wallets. Preliminary analysis of the results show that people do not have a clear mental model of electricity and tend to associate the size of the device and the duration of use with higher rates of consumption regardless of the type of device, the type of use it is put to and its actual consumption level.

charged. One explanation might be that these devices have become so ubiquitous that they, and the activities needed to support them have receded into the background.

Table 2 provides an overview of the devices that appear most frequently in the drawings created by male and female respondents. The percentages are computed per gender.

Table 2 – Electrical Devices Featured Most Frequently in Drawing 2

	Female			Male		
	Device	**Count**	**%**	**Device**	**Count**	**%**
1	Television	120	53.81	Television	116	50.66
2	Computer	86	38.57	Computer	103	44.98
3	Refrigerator	85	38.12	Refrigerator	77	33.62
4	Microwave	62	27.80	Microwave	55	24.02
5	Washing machine	41	18.39	Washing machine	35	15.28
6	Toaster	21	9.42	Radio	17	7.42
7	Hair dryer	20	8.97	Cell phone	14	6.11
8	Radio	16	7.17	Iron	14	6.11
9	Cell phone	16	7.17	Oven	13	5.68
10	Iron	15	6.73	Stereo system	11	4.80

Drawing 3 – Draw the Highest Consuming Devices

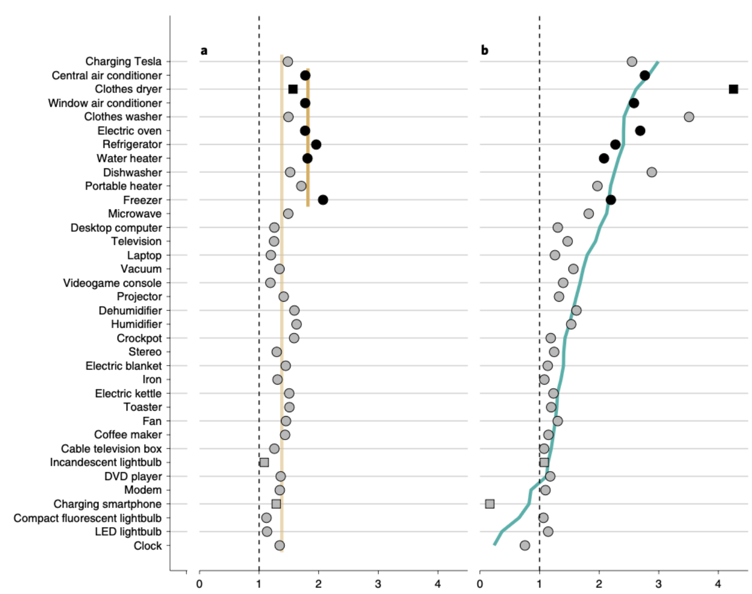
In this drawing respondents were asked to draw representations of 5 electrical devices in their homes they thought consumed the highest amount of electricity.

Although an extensive range of appliances and devices was drawn ranging from Aquariums, air compressors, alarm clocks, curling irons and cement mixers through electric guitars, humidifiers and foot massagers to sewing machines, soldering irons and water coolers those that appeared most frequently were of a more mundane nature as listed in table 3. Unfortunately the order in which the devices were drawn was not recorded so we cannot say which device was drawn first, second and so forth and only report on the total occurrence of specific devices in the drawings.

Table 3 – Top 10 Most Frequently Drawn Devices in Drawing 3

Female			Male		
Device	**Count**	**Percentage**	**Device**	**Count**	**Percentage**
Television	141	62.67	Refrigerator	154	67.25
Refrigerator	139	61.78	Television	145	63.32
Washing machine	131	58.22	Computer	127	55.46
Computer	112	49.78	Washing machine	121	52.84
Microwave	92	40.89	Microwave	102	44.54
Iron	61	27.11	Iron	56	24.45
Deep freezer	57	25.33	Light	55	24.02
Light	48	21.33	Deep freezer	42	18.34
Water heater	34	15.11	Oven	32	13.97
Tumble Dryer	32	14.22	Water heater	28	12.23

Marghetis, T., Attari, S. Z., & Landy, D. (2019). Simple interventions can correct misperceptions of home energy use. *Nature Energy*, *4*(10), 874–881. https://doi.org/10.1038/s41560-019-0467-2
https://osf.io/2qbxt/
https://www.szattari.com/publications



Effect of explicit heuristic

Effect of scale-use intervention

Fig. 2 | Effects of explicit heuristic and scale-use information interventions on energy-use estimates of home appliances. a,**b**, Comparison of mean post-intervention estimates to mean control estimates ($n=410$) for each appliance for the explicit heuristic (**a**, $n=406$) and scale-use (**b**, $n=411$) interventions. Appliances are ordered vertically, highest to lowest, by mean control estimates. Items that were not specifically targeted by the heuristic are shown in grey, and appliances that fit the heuristic's profile (large appliances that heat or cool) are shown in black. Appliances used for the scale-use intervention are indicated by squares (that is, smartphone, incandescent lightbulb, clothes dryer). **a**, Vertical orange lines indicate the mean effect of the heuristic on large appliances that heat or cool (dark) and all other appliances (light). **b**, The green line represents the predictions of an ordinary least squares regression of the scale-use intervention's effect on each appliance onto the appliance's mean control estimate.

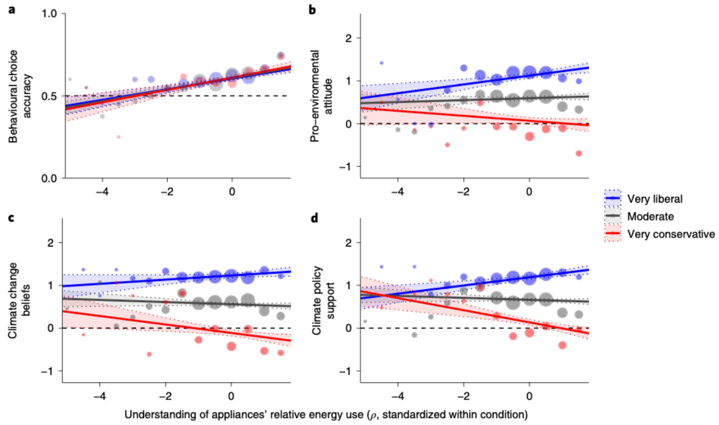


Fig. 3 | Individual differences in understanding the appliances' relative energy use. a–d, Relations between understanding the appliances' relative energy use and behavioural choice accuracy (**a**), pro-environmental attitudes (**b**), climate change beliefs (**c**) and climate policy support (**d**), illustrated with participants who reported being very liberal ($n=272$), moderate ($n=313$) and very conservative ($n=84$) in their views. (Note that analyses in the main text use all participants.) Lines indicate the model-predicted relation, thus controlling for demographic variability, with error ribbons indicating 95% CIs. Circles indicate binned means, with the circle's area indicating sample size.

accuracy: $b=0.10\pm0.05$ s.e.m., $P=0.03$), increasing the odds of success by 10%. The effect of the scale-use intervention, however, was one-fifth the size and non-significant ($M=0.60\pm0.01$ s.e.m.; effect of intervention on accuracy: $b=0.02\pm0.05$ s.e.m., $P=0.60$; see Supplementary Table 6), although a direct comparison of the two interventions was not statistically significant ($b=0.08\pm0.05$ s.e.m., $P=0.096$). Although the heuristic's benefit, averaging across all items, translated into a modest improvement in accuracy ($M=0.62\pm0.01$ s.e.m.), this benefit was greatest for those behavioural dilemmas in which a large temperature-changing appliance

a generic tendency toward more extreme numerical responses. By contrast, individual differences in understanding of the appliances' relative energy use predicted conservation behaviour: even after accounting for sociodemographic differences, one standard deviation improvement in understanding of the appliances' relative ordering was associated with taking showers that were half a minute shorter ($b=-0.40\pm0.16$ s.e.m., $P=0.01$), 1.3 times greater odds of using energy-efficient lightbulbs ($b=0.24\pm0.06$ s.e.m., $P<0.01$) and 1.3 times greater odds of owning an Energy Star-rated refrigerator ($b=0.22\pm0.07$ s.e.m., $P<0.01$), suggesting that

the US population).

Procedure. Both interventions (scale use and explicit heuristic) were fully crossed between participants and randomly assigned. Following past work[3], we reminded all participants that a 100-W incandescent lightbulb uses 100 units of energy in 1 h (that is, 100 Wh). In the scale-use intervention condition ($n=411$), participants were informed about two additional appliances that they could use to calibrate their energy estimations: "A 5-watt phone charger uses 5 units of energy to charge a smartphone in one hour" and "a typical clothes dryer uses about 4,000 units of energy in one hour". In the explicit heuristic condition ($n=406$), participants were informed that "large appliances that primarily heat or cool things use a lot more energy than people think". The remaining participants received no intervention ($n=410$) or both interventions ($n=418$), with the scale-use information presented first.

After receiving this information, participants completed the energy estimation task in which they estimated the hourly energy use of a range of 36 home appliances (for example, water heater, dehumidifier, laptop computer, washing machine, central air conditioner, and others) ordered randomly for each participant. Estimates were in energy units equivalent to watt-hours. (See Supplementary Tables 9 and 10 for mean estimates and errors for each appliance, by condition.) After completing the estimation task, participants reported overall confidence in their estimates on a four-point scale and supplied open-ended descriptions of how they estimated the energy use of washing machines and projectors.

We then investigated a suite of conservation-relevant behaviours, attitudes and beliefs. First, we evaluated participants' ability to make a pairwise choice between hypothetical conservation-related behaviours. Participants again received the intervention associated with their condition (that is, the scale-use information, the heuristic, both or neither). They then completed 20 pairwise choices in which they had to choose the task or activity that would use the least amount of electricity, or the behavioural change that would lead to the greatest energy conservation. For instance, one item required choosing between watching a movie on a laptop or using a projector.

Second, we asked a series of questions that are part of an ongoing project on the perception of national energy systems rather than home energy. These questions related to the sources of energy used in the United States and the difference between electricity and energy. We do not analyze the responses here.

Third, we measured participants' attitudes and beliefs about climate policy

Third, we measured participants' attitudes and beliefs about climate policy, climate change, and the environment. We evaluated support for climate policies by asking participants to indicate, on a scale from 1 (strongly oppose) to 4 (strongly support), whether they support or oppose three climate policies, averaged to create a single measure of policy support ($M = 3.3 \pm 0.02$ s.e.m.; Cronbach $\alpha = 0.83$): (1) fund more research into renewable energy sources, such as solar and wind power; (2) regulate carbon dioxide (the primary greenhouse gas) as a pollutant; and (3) require electric utilities to produce at least 20% of their electricity from wind, solar or other renewable energy sources, even if it costs the average household an extra $100 a year. Using the same 1–4 scale, we evaluated participants' climate change beliefs[41], including whether climate change is happening, how sure they are that it is happening, and whether climate change is an important issue to them personally, averaged to create a single measure ($M = 3.3 \pm 0.02$; Cronbach $\alpha = 0.87$). We also evaluated pro-environmental attitudes with the 15-item Revised New Ecological Paradigm scale[42], ranging from 1 (strongly disagree) to 5 (strongly agree) ($M = 3.7 \pm 0.02$, Cronbach $\alpha = 0.89$).

Fourth, participants completed two assessments of numeracy[43,44]; the mean accuracy on both assessments was summed to create a single measure of numeracy ($M = 1.03 \pm 0.01$, Cronbach $\alpha = 0.87$).

Fifth, we asked about participants' current energy-conservation behaviour: the percentage of energy-efficient bulbs in the home, whether they have an Energy Star-rated refrigerator, and the length of time they showered. These questions were used to assess the relation between energy-use estimation skills and current real-world behaviours. We also asked about hypothetical thermostat settings, but the answers are not analyzed here because many respondents gave unrealistic or uninformative responses (for example, cooling the house to 0 °F).

Finally, we asked a series of sociodemographic questions: gender; age; highest level of education attained; whether they had college training in physics, engineering or mathematics; whether they had training as an electrician; political ideology, from very liberal to very conservative; income; and ZIP code. There were no other measures or manipulations. The survey text is available in the Supplemental Methods.

Analysis. For tasks with multiple responses from each participant, we used mixed-effects models with random effects for participants and items; otherwise, we used multiple regression. Models were implemented in the R statistical programming environment[45], and mixed-effects models were fit using the lme4 package[46]. A logistic linking function was used for binary responses (for example, owning an Energy Star-rated refrigerator). Both the actual and the participants' estimates of an appliance's energy use were $\log_{10}$-transformed, which is in line with past work that the mental representation of quantities, and energy estimates in particular, is logarithmic[3,11]. The actual energy use was calculated from a sample of appliances found online and in local stores (see Supplemental Data).

The models controlled for measures of sociodemographic and individual differences (for example, gender, age, education, numeracy). All dichotomous predictors were dummy coded as follows: (1) interventions: did not receive, 0; did receive, 1; (2) male: yes, 1; no or other, 0; (3) electrician: no, 0; yes, 1; (4) relevant degree: no, 0; yes, 1. Sociodemographic measures were mean centred; political ideology was centred at the liberal end of the spectrum, so regression coefficients reflect the effect of being one point more conservative (range = [0,6]); all other predictors were mean centred and standardized (that is, z-scored). For full model specifications, see Supplementary Note 1 for analyses of the energy estimates, Supplementary Note 2 for analyses of current conservation behaviour, and Supplementary Note 3 for analyses of pairwise behavioural choices. The reported P values are two-sided. The mediation analyses used a quasi-Bayesian Monte Carlo method[47].

One participant was removed from the analysis for giving identical energy estimates for all appliances. One additional participant was removed from the analysis of shower length time for reporting a typical shower length of longer

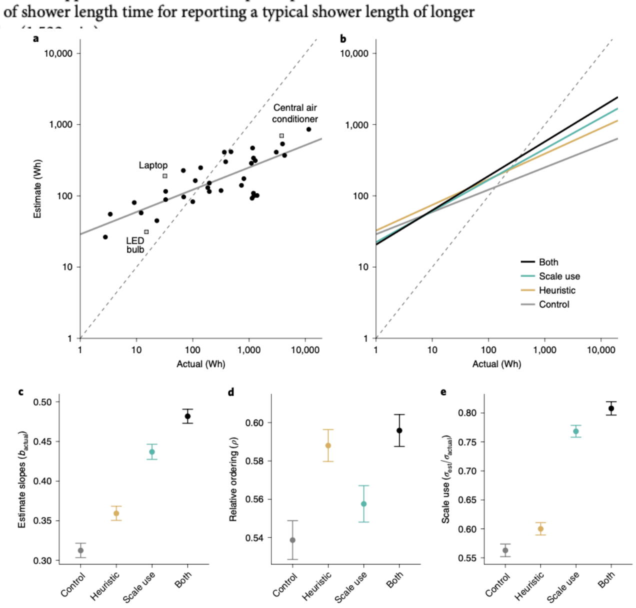


Fig. 1 | Relation between actual and estimated energy use. a, Energy estimates in the control condition for 36 home appliances ($n=410$). The solid grey line indicates the relation between actual and estimated energy use (on a log-scale). The dashed line illustrates perfect estimation performance: a slope of 1 between actual and estimated values. **b**, Relation between actual and estimated energy use for 36 home appliances in the control group ($n=410$), in the group that received the explicit heuristic intervention (orange line; $n=406$), in the group that received the scale-use intervention (green line; $n=411$) and in the group that received both interventions (black line; $n=418$). The dashed line ($y=x$; slope of 1) illustrates perfect estimation performance. **c**, Estimate slopes for participants in each condition. **d**, Correlation between estimated and actual energy use. **e**, The ratio between the standard deviation of individuals' estimates and the standard deviation of the actual values. Points and error bars indicate means ± s.e.m.

Lesic, V., Glasgo, B., Krishnamurti, T., Bruine De Bruin, W., Davis, M., & Azevedo, I. L. (2019). Comparing consumer perceptions of appliances' electricity use to appliances' actual direct-metered consumption. *Environmental Research Communications*, *1*(11), 111002. https://doi.org/10.1088/2515-7620/ab4a99

CrossMark

OPEN ACCESS

RECEIVED
13 May 2019

REVISED
25 September 2019

ACCEPTED FOR PUBLICATION
3 October 2019

PUBLISHED
21 October 2019

LETTER

Comparing consumer perceptions of appliances' electricity use to appliances' actual direct-metered consumption

Vedran Lesic[1,6], Brock Glasgo[2], Tamar Krishnamurti[2,3], Wändi Bruine de Bruin[1,2], Matthew Davis[4] and Inês Lima Azevedo[5]

[1] Centre for Decision Research, Leeds University Business School, United Kingdom
[2] Engineering and Public Policy, Carnegie Mellon University, United States of America
[3] General Internal Medicine, University of Pittsburgh School of Medicine, United States of America
[4] Socio-Technical Center, Leeds University Business School, United Kingdom
[5] Department of Energy Resources Engineering, School of Earth, Energy & Environmental Science, Stanford University, United States of America
[6] Author to whom any correspondence should be addressed.

E-mail: vedran.lesic7@gmail.com, bpglasgo@gmail.com, tamark@pitt.edu, w.bruinedebruin@leeds.ac.uk, m.davis@leeds.ac.uk and iazevedo@stanford.edu

Keywords: consumer perceptions, residential, energy efficiency

Supplementary material for this article is available online

Abstract

Many strategies for reducing residential energy consumption—including product labelling programs, subsidies for the purchase of efficient devices, behavioral programs that encourage efficient energy use, and others—rely on building owners and end users to make informed investment and operational decisions. These strategies may be ineffective if consumers are unaware of how much electricity is used by different devices in their homes and buildings. This study therefore compares consumers' perceptions of their appliances' electricity use to these appliances' actual direct-metered electricity consumption. Using an online survey, 118 homeowners from Austin, Texas were asked to estimate the energy consumption of six household devices which were monitored in the participants' homes. Homeowners were randomly assigned to assess their appliance-specific electricity use in terms of energy units (kWh/month) or energy cost units ($/month) for an average summer month. Consistent with previous studies, participants overestimated the energy consumed by their low energy consuming devices and slightly underestimated that of their most energy-consuming device. Results also showed that responses of the experimental groups estimating their consumption in energy units and energy cost units were similar, the accuracy of the two groups' perceptions was similar, and levels of confidence in the two groups were similar. These results suggest that targeted information campaigns focused on air conditioning energy consumption and device power reduction opportunities could improve consumer decision-making to save energy and reduce demand.

Here, we present the first study to evaluate whether consumers have more accurate perceptions of their devices' energy consumption when giving their assessments in energy units or energy cost units. To account for variation in energy consumption between homes, device-level submeter electricity use data from the study participants' homes are combined with results from an online survey administered to these same homeowners. Because our study focused on a diverse set of specific household appliances that are commonly used, our findings will be uniquely actionable for policy and program designers responsible for designing programs and information campaigns aimed at reducing household energy use.

The study explores the following research questions:

1. Do consumers give more accurate estimates of their devices' energy use when they report in energy units versus energy cost units?

2. Do consumers give more accurate ranks of their devices' energy use when they report in energy units versus energy cost units?

3. Are consumers more confident in their perceptions when reporting in energy units versus energy cost units?

2.2. Survey design

A link to an online survey was emailed by the Pecan Street Research Institute to 310 qualifying participants and was open from October 24 through November 28, 2014. The survey posed questions aimed at eliciting homeowners' understanding of their devices' energy consumption. Here, we describe the questions relevant to the presented analyses.

All participants were randomized to estimate—in either energy units (kWh/month) or energy cost units ($/month)—the electricity consumption of their clothes washers, dishwashers, ovens, clothes dryers, refrigerators, and air conditioners. These six devices were chosen as they are common in American households, they vary significantly in their monthly energy consumption, they are widely submetered in the Pecan Street households, and they account for approximately 50% of total household electricity use. The survey asked participants to consider their usage of these devices during an average summer month as they responded. The summer months were chosen because air conditioning consumption is the highest and does not vary significantly month-to-month over during this time period.

Following previous work [6], the energy units and energy cost units experimental groups were provided with a reference point which explained that a 100-Watt incandescent light bulb used for one hour per day for 30 days would consume 3 kWh or $0.30 of electricity, respectively. Depending on their randomly assigned experimental group, they were then asked to estimate the electricity *consumption* or electricity *cost* of those six devices by sliding a bar along an axis to indicate lower or higher energy consumption. End points were chosen to be nearly equivalent in both groups and were labeled 0 and 1000 kWh and $0 and $100 for the energy units and energy cost units groups, respectively. If a participant did not have one of the appliances, they could select 'not applicable'. Next, participants were asked to indicate their level of confidence about the estimates of their devices' energy consumption they provided in the previous task by selecting from four possible options ranging from 'I believe I correctly judged all the appliances' to 'I pretty much had to guess the electricity use of all the appliances'. Participants were then asked to explain the rationale behind their estimates by entering a short description.

Finally, participants answered questions about their electricity bills, participation in efficiency programs, and their use of their online energy dashboard displays. Near the end of the survey, participants answered socio-demographic questions about their age, sex, level of income, level of education and number of adults and children in the home. Complete copies of both surveys can be found in appendix B.

2.3. Survey responses

A total of 130 responses were recorded for a response rate of 42%. Homes with incomplete energy use data for June through August of 2014 were excluded, resulting in a final sample size of 118 responses. All participants gave informed consent, and were offered a $5 Amazon voucher for completing the online survey.

Of the final sample, 94% had at least a college degree, 81% were Caucasian, and 61% of those completing the

Table 1. Summary statistics of the annual electricity use of Pecan Street and Department of Energy standard homes.

	Pecan street		Department of energy	
Energy use	Mean	SD	Mean	Source
Whole-home (kWh yr^{-1})	11,400	7,100	16,500	[15]
AC condensing unit (kWh yr^{-1})	3,500	2,400	5,400	[15]
Refrigerator (kWh yr^{-1})	1,300	2,000	1,400	[15]
Electric clothes dryer (kWh yr^{-1})	490	300	1,000	[16]
Oven (kWh yr^{-1})	190	140	820	[17]
Dishwasher (kWh yr^{-1})	120	150	120	[16]
Clothes washer (kWh yr^{-1})	50	50	110	[16]

2.4. Electricity use data

Whole-home and device-level electricity use data were downloaded from the Pecan Street Inc.'s online Dataport database [14]. These data were generated by submeters installed in each home and made available to researchers. Hourly interval data were downloaded and summed to calculate monthly electricity consumption for each appliance.

Annual electricity consumption for the homes and devices in this study are summarized in table 1. Also shown are Department of Energy (DOE) estimates of the electricity consumed by standard homes and appliances. Whole-home consumption estimates were taken from the EIA's Residential Energy Consumption Survey (RECS) and represent similar single-family homes in Texas with central air conditioning, similar to those in the Pecan Street sample.

These values show that Pecan Street consumers used less energy on average than consumers in similar Texas homes, both at the whole-home level and for specific devices. Glasgo *et al* [18] found similar differences between the energy consumption of the Pecan Street homes, other residential customers served by the same electric utility provider, and Texas homes included in the RECS. The same study [18] also found that Pecan Street homes were on average smaller, had fewer occupants, and had much higher household incomes compared to the regionally representative sample included in the RECS.

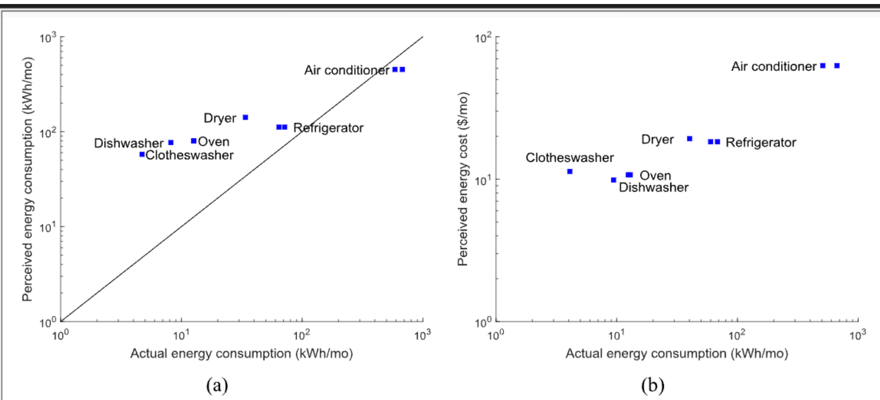


Figure 1. Scatterplots showing actual mean energy consumption on the *x*-axis and mean perceived energy consumption on the *y*-axis for (a) participants responding in energy units, and (b) participants responding in energy cost units. The diagonal shows perfect agreement. All values shown are averages.

Estimated energy consumption and estimated energy costs were compared to actual consumption by calculating Spearman rank correlations which compare the ordinal rankings of devices inherent in participants' estimates and the actual ordinal rankings of the devices based on metered energy use data. The average Spearman rank correlation in the energy units group was $\rho = 0.82$ (SD = 0.32), and the average in the energy cost units group was $\rho = 0.76$ (SD = 0.38). A two-tailed t-test shows no difference in the Spearman rank correlations calculated for the two experimental groups ($t(106) = 0.86, p > .05$). Thus, the format of reporting units did not significantly affect the accuracy of participants' perceptions of their electricity use for different appliances.

When asked to briefly explain how they generated their estimates, many participants mentioned their frequency of interaction with individual devices and the overall amount of time devices are in operation. Far fewer mentioned the power those devices require to operate. Details can be found in appendix C.

Analysis of individual perceptions show skewed distributions with modes at or near zero error for all six devices. Thus, many participants had very accurate perceptions of their energy consumption. The overall average errors seen in figure 1 are the result of relatively few responses with large, consistent over- or underestimates. Details can be found in appendix D.

3.2. Accuracy of ranks

Using the same Spearman rank-ordering method, average participants' rankings for appliances' energy use were compared to rankings of appliances' actual use for the two experimental groups in figure 2. Appliances are listed from left to right in order of increasing rank. Average rankings by the energy units group increased in line with appliances' increasing energy consumption. However, participants in the cost units group typically ranked the three least energy-consuming devices incorrectly. Kendall's tau tests comparing appliance rankings between the two test groups show no statistically significant differences ($p > 0.05$ for all appliances). The apparent differences between these rankings and those which can be deduced from the scatterplots above are the result of individual misperceptions affecting the averages shown in figure 1.

3.3. Confidence in perceptions

Figure 3 shows participants' reported confidence.

Univariate ANOVA was computed in order to examine the effects of reporting units on participants' ratings of their confidence. The main effect of reporting units conditions, $F(1, 115) = 0.23, p > .05$ was not significant. This means that there was no significant difference in levels of reported confidence among participants. Comparing reported confidence to the Spearman rank correlations for households in each category shows that participants with higher confidence in their responses did indeed have more accurate perceptions as seen in appendix E.

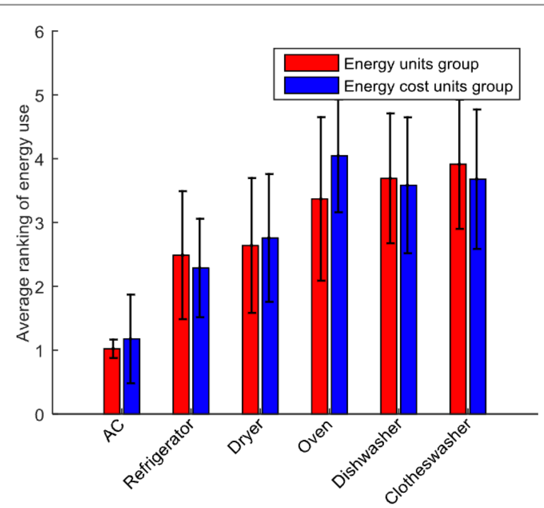


Figure 2. Average ranking of devices by perceived energy consumption. Error bars show ±1 standard deviation. Appliances are listed from left to right by average annual energy consumption. A rank of 1 corresponds to the most energy consuming device, and 6 corresponds to the least consuming device.

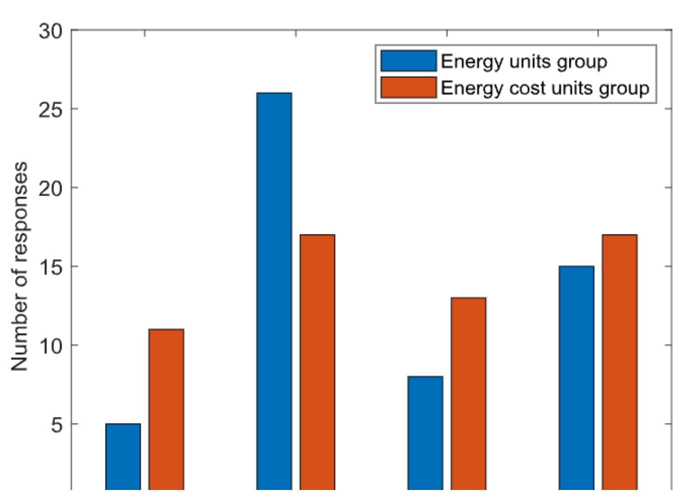


Figure 3. Participants' reported confidence in their estimates of device-level energy consumption.

https://iopscience.iop.org/article/10.1088/2515-7620/ab4a99/pdf

Participants' focus on the amount of time devices are operating rather than the combination of time and power aligns with the findings of Attari *et al* [6], which found that people associated energy savings more with reducing the time that devices were operating than replacing the device with a more efficient version. Both findings suggest that consumers fail to fully appreciate the effect that device power has on energy consumption.

The main limitation of this research design is the use of a convenience sample. All participants in this study are volunteers in the Pecan Street Research Institute's submetering study that allows them to access detailed online summaries of their whole-home and device-level electricity use. These homeowners represent early adopters of energy services who are highly educated, relatively wealthy, and predominantly white. This population has also undergone several energy-related interventions and studies which make them much more energy-conscious and knowledgeable than average consumers. Most prominently, the surveyed households have access to online portals which provide homeowners the exact information this survey was intending to have participants estimate. Many participants reported checking their online feedback energy reports. Thus some of the responses are a result of direct knowledge of their devices' energy consumption and the overall accuracy of the responses is overestimated.

Our results highlight the difficulty of building and maintaining the kind of consumer energy awareness that would enable efficiency-promoting investment and operational decisions. Even energy-conscious homeowners with access to reports of their devices' energy consumption have misperceptions about their devices' energy consumption. The patterns of these misperceptions confirm the results of previous studies, indicating that data based on estimates from existing data sources and previous literature could be used as a reliable proxy for real-time measured electricity use. That these misperceptions still exist even in a population with access to metered device-level energy consumption data proves how persistent they are.

Understanding consumers' misperceptions can help to inform the design of policies and programs that will allow consumers to make their homes consume less energy. Consistent in this study and Attari *et al* [6] is an underestimation of the energy consumed by central air conditioning systems. These systems present several behavioral and technological opportunities for homeowners to reduce their energy consumption through measures such as improved controls and setbacks, building envelope improvements, and regular preventive maintenance. Well-designed information campaigns to inform homeowners of their systems' consumption, their options for reducing that consumption, and the expected cost savings from those reductions would likely increase adoption of efficiency and conservation measures. Such campaigns may benefit from segmentation of consumers to target certain populations prone to large misperceptions. More generally, consumers should be made more aware of the concept of power in determining energy consumption as our survey results show this understanding is lacking. Previous behavioral programs have focused on the amount of time that energy-consuming devices are in use—turning off lights, unplugging devices not in use, etc—but fail to address the potential savings that can be had from power-reducing measures. Building this understanding and providing practical information on how to reduce power—by changing device settings, choosing lower-power devices, etc—would enable more energy-conscious decision-making and allow homeowners to reduce their energy consumption, their energy bills, and their homes' environmental footprint.

https://iopscience.iop.org/article/10.1088/2515-7620/ab4a99

▲ Hide supplementary data

Supplementary data (1.05 MB PDF)

U.S. Consumer Attitudes Towards Appliance Efficiency Standards and Purchasing Behaviors by Income, Race, and Homeownership

U.S. Consumer Attitudes Towards Appliance Efficiency Standards and Purchasing Behaviors by Income, Race, and Homeownership

Overview
Metadata
Files
OSF Storage
Wiki
Components
Analytics
Registrations

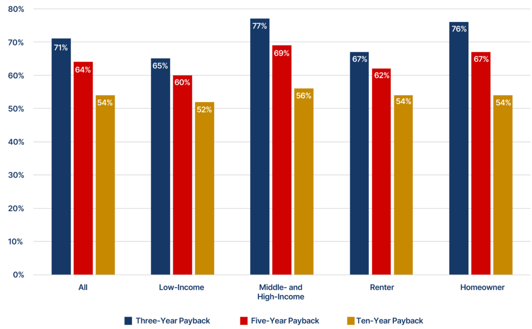
OSF Storage

Filter: Filter current list
Sort by: Name: A-Z
Download this folder

Annex A Methodology and Data Tables	1 Download	235.5 kB	2023-01-18 01:15 PM	⋮
Issue Brief	1 Download	2.5 MB	2023-01-18 01:13 PM	⋮
license.txt	0 Downloads	20.1 kB	2023-01-18 01:26 PM	⋮

FIGURE 2. SUPPORT FOR APPLIANCE EFFICIENCY STANDARDS WITH THREE, FIVE, AND TEN YEAR PAYBACK PERIODS

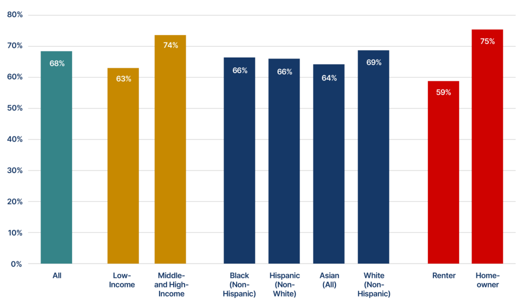
Sorted by Income and Homeownership Status (Renter vs. Owner)



Note: We define support as the proportion of respondents that replied "strongly support" or "somewhat support".

FIGURE 4. PERCENTAGE OF RESPONDENTS THAT HAVE HAD AT LEAST ONE MAJOR APPLIANCE REPLACED WITHIN THE LAST FIVE YEARS

Sorted by Income, Race, and Homeownership Status (Renter vs. Owner)



Note: This study defines a major appliance as a refrigerator, clothes washer, water heater or major space heating equipment/system.

FIGURE 5. MAJOR REASON FOR PRODUCT REPLACEMENT (REFRIGERATORS AND CLOTHES WASHERS)

Sorted by Income, Race, and Homeownership Status (Renter vs. Owner)

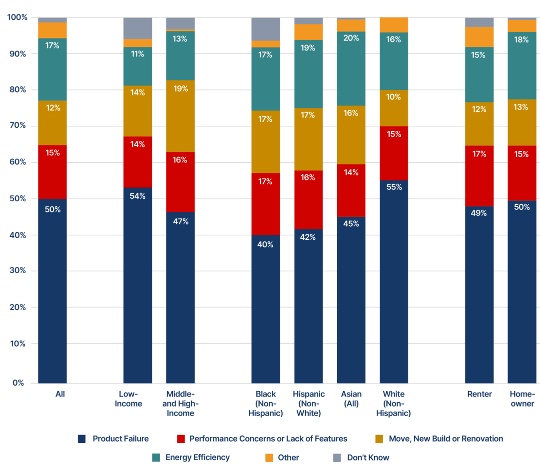
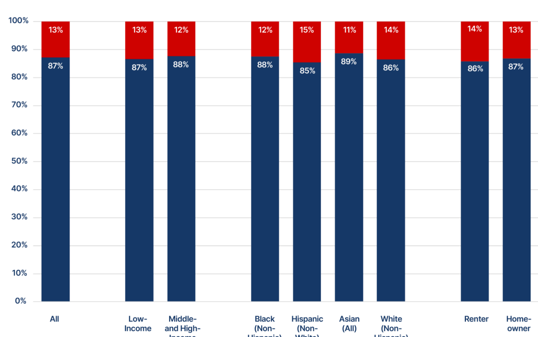


FIGURE 7. IMPORTANCE OF ENERGY EFFICIENCY IN LAST MAJOR APPLIANCE PURCHASE

Sorted by Income, Race, and Homeownership Status (Renter vs. Owner)



Important Not Important

Note: We define energy efficiency as an important factor in a respondent's last major appliance purchase if they indicated it was "very important" or "somewhat important" in their decision.

Annex A Methodology and Data Tables.pdf
Page 5 of 9

AA7. What was the major reason for the replacement of your refrigerator? (Base = Refrigerator has been replaced in past five years)

	All US Adults	Low-Income	Middle-and High-Income	White	Black/African American	Hispanic	Asian	Renters	Homeowners
Unweighted Base	1536	626	910	956	192	445	88	478	915
Product Failure (%)	45	50	5	49	36	39	46	45	45
Performance Concerns or Lack of Features (%)	16	14	14	16	18	18	19	18	16
Energy Efficiency (%)	13	11	11	10	18	18	17	12	15
Move, New Build, or Renovation (%)	18	15	15	18	17	17	2	16	20
Other (%)	5	7	7	5	7	5	3	6	4
Don't Know (%)	2	3	3	2	2	2	0	3	1

AA8. When your refrigerator was replaced, was it replaced with a new or used product? (Base = Refrigerator has been replaced in past five years)

	All US Adults	Low-Income	Middle-and High-Income	White	Black/African American	Hispanic	Asian	Renters	Homeowners
Unweighted Base	1536	626	910	956	192	445	88	478	915
New (%)	84	74	74	86	74	79	47	70	93
Used (%)	15	23	23	13	21	19	9	27	7
Don't know (%)	1	2	2	1	4	2	0	3	0

Zanocco, C., Sun, T., Stelmach, G., Flora, J., Rajagopal, R., & Boudet, H. (2022). Assessing Californians' awareness of their daily electricity use patterns. *Nature Energy*, *7*(12), 1191–1199. https://doi.org/10.1038/s41560-022-01156-w
https://osf.io/4jxcm/
https://static-content.springer.com/esm/art%3A10.1038%2Fs41560-022-01156-w/MediaObjects/41560_2022_1156_MOESM1_ESM.pdf

a 'Choose the graph most likely to represent your home's electricity use on weekdays (Monday–Friday) before your household made any changes due to shelter-in-place orders related to COVID-19 (coronavirus)...'

b 'Now choose the graph most likely to represent your home's electricity use on weekdays (Monday–Friday) since your household made any changes due to shelter-in-place orders related to COVID-19 (coronavirus)...'

c

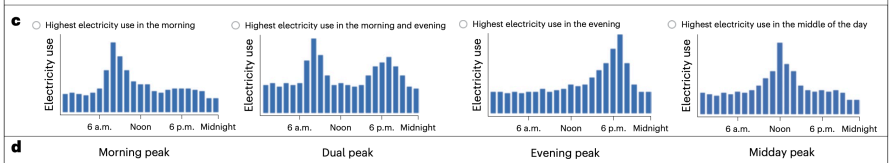


Fig. 1 | Questionnaire with response choices for perceived weekday electricity use patterns. a, The survey question that assesses perceived dominant load shape before SIP. **b,** The survey question that assesses perceived dominant load shape during SIP. **c,** For **a** and **b**, participants chose one of the load shapes from **c** as a question response. For **b**, participants also had the option of choosing 'My household has not made any changes due to shelter-in-place orders related to COVID-19 (coronavirus)'. **d,** The load shape designation assigned to each response choice from **c** for comparison to observed load shapes.

selecting among various time-of-use rate pricing programmes and responding to critical peak hours; taking advantage of incentives for residential solar, storage and electrical vehicle adoption; adopting smart home devices; enrolling in programmes that afford utilities some control over their appliance use; and managing the day-to-day timing of large loads (for example, electric vehicle charging, laundry and so on).

Scholars have delineated many different types of energy literacy, including device (that is, knowledge of appliance- or device-level energy consumption), action (that is, knowledge of the energy savings associated with particular actions) and financial (that is, knowledge about monetary savings associated with energy savings investments) energy literacies[12–15]. 'Multi-faceted' energy literacy incorporates broader concepts in addition to these more 'practical' measures—including cognitive or content knowledge (for example, about sources of electricity generation, societal impacts), affective components

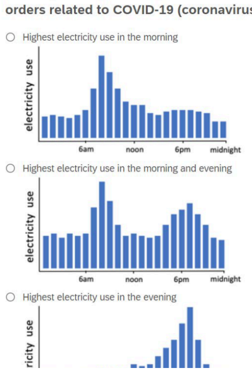
evening peak[21]. This frequent residential load shape coincides with California's system peak period and is a motivation for why utilities have begun charging higher prices to residential customers during the evening (for example, time of use)[23].

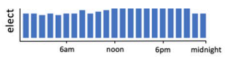
To assess our respondents' load shape awareness, we compared survey questionnaire responses about perceived dominant daily load shapes (morning peak, evening peak, midday peak and dual peak; Fig. 1) to observed daily load shapes calculated from their smart meter data. When these shapes align, we consider the participant as having awareness about their load shape. Due to the timing of our survey, we were also able to assess how a disruptive event that had broad impacts on nearly every household in California, shelter-in-place (SIP) orders in response to the COVID-19 pandemic, influenced perceptions of energy use patterns in the home. Past research has highlighted the importance of disruptive life events (for example, moving, birth of a child) in alter-

Supplementary Note 4: Survey questions applied in the study

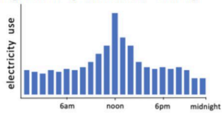
Q1. Before shelter-in-place perceived load shape

Choose the graph **most likely** to represent your home's electricity use on **weekdays** (Monday - Friday) **before** your household made any changes due to **shelter-in-place orders related to COVID-19 (coronavirus)**.





○ Highest electricity use in the middle of the day

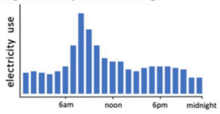


Q2. After shelter-in-place perceived load shape

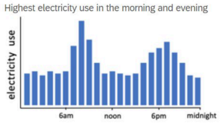
Now choose the graph **most likely** to represent your home's electricity use on **weekdays** (Monday-Friday) **since** your household made any changes due to **shelter-in-place orders related to COVID-19 (coronavirus)**.

○ My household has not made any changes due to shelter-in-place orders related to COVID-19 (coronavirus).

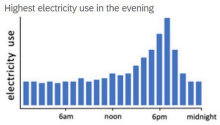
○ Highest electricity use in the morning



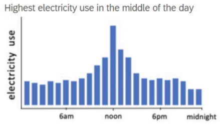
○ Highest electricity use in the morning and evening



○ Highest electricity use in the evening



○ Highest electricity use in the middle of the day



Q3. Rate plan

Which of the following best describes the rate you pay for electricity?

○ Flat rate. The price of electricity is always the same.

○ Tiered rate. The price of electricity increases as I use more electricity during the billing cycle.

○ Time-based rate. The price of electricity changes at different times of day. This is usually called "Time-of-Use" or "Time-of-Day" pricing.

○ Other (please specify):

○ I don't know.

Supplementary Note 1: Data description and summary statistics

Supplementary Table 1 contains information about household electricity data and survey data provided by study participants. Supplementary Table 2 provides summary statistics for demographic and household characteristics as well as a comparison to estimates from the American Community Survey. Supplementary Table 3 provides a comparison of participants with solar vs. those without solar systems across load shape perception measures.

Supplementary Table 1: Household electricity data and respondent survey data summary.

	Data sources		Sources of excluded data (n)				
	Derived from electricity data	**Derived from survey data**	**Households with missing electricity data[1]**	**Households missing survey data[2]**	**Households missing survey & electricity data**	**Households with solar**	**Analytical sample (n)**
Study participants							242
Observed load shapes	Yes	No	18			26	198
Perceived load shapes	No	Yes		15			230
Observed load shapes & perceived load shapes	Yes	Yes	15	12	3	26	186
Demographic/ household characteristics	No	Yes		26			219
Observed load shapes & perceived load shapes & demographic/ household characteristics	Yes	Yes	13	21	5	26	177

[1]Insufficiency of hourly interval coverage across study period, sensor reading errors, instances of negative hourly demand, or

evidence of no household occupancy
²Participant did not respond to survey item on the questionnaire

Kanay, A., Hilton, D., Charalambides, L., Corrégé, J.-B., Inaudi, E., Waroquier, L., & Cézéra, S. (2021). Making the carbon basket count: Goal setting promotes sustainable consumption in a simulated online supermarket. *Journal of Economic Psychology*, *83*, 102348. https://doi.org/10.1016/j.joep.2020.102348
https://osf.io/nzce9/?view_only=c44391bb020c4a799e93d49b614a0c14
https://ars-els-cdn-com.proxyiub.uits.iu.edu/content/image/1-s2.0-S0167487020301057-mmc1.pdf

6.1.2. Procedure

Upon arrival at the Toulouse School of Economics experimental laboratory participants were randomly assigned to sit in front of one of a suite of laptop computers, separated from each other by a board, which prevented them from seeing how others are responding. Participants were assigned to the experimental conditions and after having read the instructions, they immediately proceeded to their shopping visit. As in the previous experiments, participants were informed that they disposed of a 25€ budget and that they had to spend minimum of 20 euros to be able to leave the shopping platform. They were also told that the unspent part of the budget would not be returned to them.

Participants could make either one or three visits. This was clarified in the beginning of the experiment. Participants who did three visits saw a page saying, "You are going to do your visit once again. Imagine that your last visit is about one week ago." between the visits. As in the previous experiments, participants were informed that they had 1 chance out of 5 of winning the basket of products they selected. After having finished the experiment, participants who did one visit rolled a dice to determine whether they would receive the basket they ordered and participants who did three visits rolled the dice three times, once for each basket selected to determine whether they would receive the basket or baskets they ordered. This procedure enabled us to augment the ecological validity of the experimental design and encourage the expression of participants' true preferences on all visits. After finishing their shopping, participants proceeded to answer the same series of questions as in the first two studies, but also responded to a carbon footprint knowledge questionnaire, which was presented prior to the final socio-demographic questions.

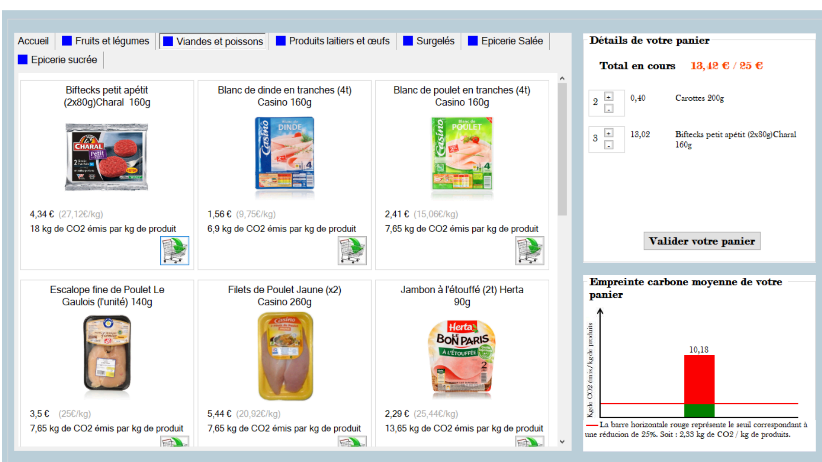
6.1.3. Measures

As in Studies 1 and 2, we administered an adapted version of the EAI-S (Milfont & Duckitt, 2010), asked questions about purchasing criteria and habits, familiarity with online shopping and socio-demographics.

Participants were required to estimate the carbon footprint of 36 products selected from the food catalogue of *GreenShop 2* as high, medium or low (see Appendix G for an example of an item). A default response category "I do not know" was also provided to the participants. For each of the 6 categories (fruits and vegetables, meats and fish, dairy products and eggs, frozen foods, sweet goods, and savoury goods), representative products were included in the questionnaire. Products coming from other countries were not included in order to eliminate possible use of the food-mile heuristic (Sale, 2012). Similarly, organic products were excluded from the questionnaire. The order of the products was randomly generated and an informative paragraph about carbon footprint was displayed before starting the questionnaire. An error score was calculated such that lower scores showed that participants' answers were closer to the correct answers and thus more accurate.

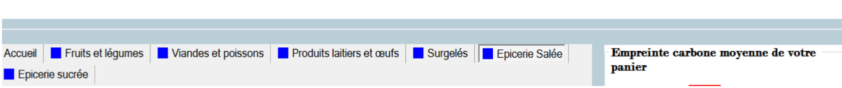
Appendix D

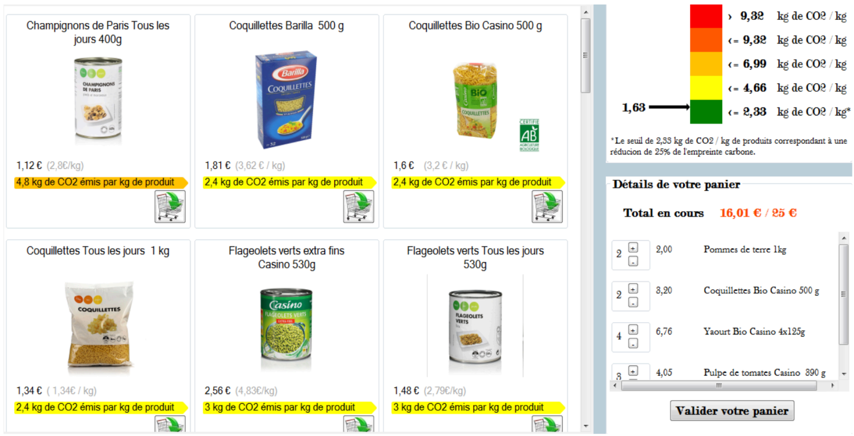
Graphical Thermometer Goal Setting Condition with Example of a Basket Exceeding Sustainable Threshold



Appendix F

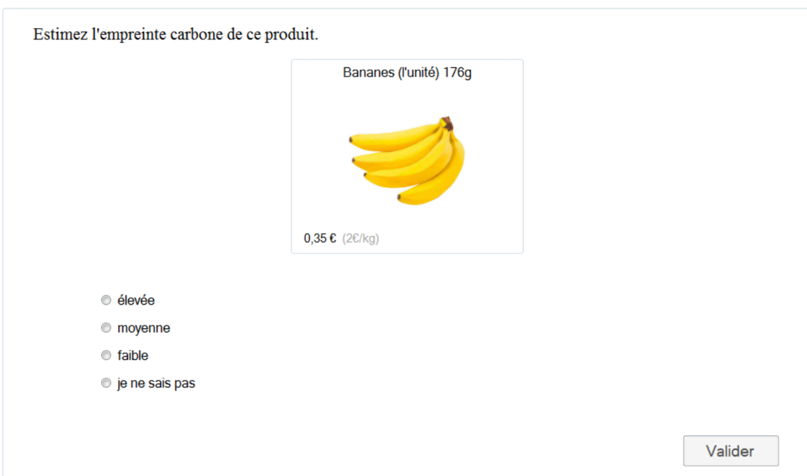
Multi-coloured Thermometer Goal Setting Condition with Example of a Shopping Basket Respecting the Sustainable Level





Appendix G

Example of an Item In Carbon Footprint Knowledge Survey



https://www.szattari.com/publications

SHAHZEEN ATTARI

ABOUT PUBLICATIONS LAB COURSES MEDIA OUTREACH

Publications

Muddling through Climate Change: A Qualitative Exploration of India and U.S. Climate Experts' Perspectives on Solutions, Pathways, and Barriers
Landon Yoder, Alora Cain, Ananya Rao, Nathaniel Geiger, Ben Kravitz, Mack Mercer, Deidra Miniard, Sangeet Nepal, Thomas Nunn, Mary Sluder, Grace Weiler & Shahzeen Z. Attari (2024) *Sustainability 16*, 5275.

- SI Text

Recycling bias and reduction neglect

Michaela J. Barnett, Patrick I. Hancock, Leidy E. Klotz & Shahzeen Z. Attari (2023) *Nature Sustainability* 6, 1418–1425.

- SI Text
- Data

Enabling an equitable energy transition through inclusive research (Comment)
A. P. Ravikumar, E. Baker, A. Bates, D. Nock, D. Venkataraman, T. Johnson, M. Ash, S. Z. Attari, K. Bowie, S. Carley, S. Castellanos, M. Cha, D. L. Clark, D. Deane-Ryan, D. Djokic, J. C. Ford, A. Goldstein, E. Grubert, L. Hu, D. M. Kammen, U. Kosar, C. Miller, M. Pastor and M. Tuominen (2022) *Nature Energy* 8, 1–4.

Young adults face the future of the United States: perceptions of its promise, perils, and possibilities
Joseph Kantenbacher, Deidra Miniard, Nathan Geiger, Landon Yoder, Shahzeen Z. Attari (2022) *Futures*, Volume 139, 102951.

- Survey
- Data

Turning a coal state to a green state: Identifying themes of support and opposition to decarbonize the energy system in the United States
Deidra Miniard and Shahzeen Z. Attari (2021) *Energy Research and Social Science*, Volume 82, 102292.

- SI Text
- Data

Reorienting climate decision making research for smallholder farming systems through decision science
Kurt B. Waldman, Zack Guido, Peter M. Todd, Tom P. Evans, Amanda Carrico, and Shahzeen Z. Attari (2021) *Current Opinion in Environmental Sustainability,* 52, 92-99.

Investigating similarities and differences in individual reactions to the COVID-19 pandemic and the climate crisis
Nathan Geiger, Anagha Gore, Claire Squire, Shahzeen Z. Attari (2021) *Climatic Change* 167.

- OSF (data, R code rmd, Survey)

Moderating spillover: Focusing on personal sustainable behavior rarely hinders and can boost climate policy support
Gregg Sparkman, Shahzeen Z. Attari and Elke U. Weber (2021) *Energy Research & Social Science*, 78.

- Survey & Supplemental Information
- Data (file1 and file2)

Transforming energy use
Shahzeen Z. Attari (2021) *Current Opinion in Behavioral Sciences* 42, 104–108.

Better rules for judging joules: Exploring how experts make decisions about household energy use
Joseph Kantenbacher and Shahzeen Z. Attari (2021) *Energy Research and Social Science*, Volume 73, 101911.

- Supplemental Information
- Quantitative data

Shared vision for a decarbonized future energy system in the United States
Deidra Miniard, Joseph Kantenbacher, and Shahzeen Z. Attari (2020) *Proceedings of the National Academy of Sciences,* 117 (13) 7108-7114.

- Supplemental Information
- Data
- R Code (RMD)

Credibility, communication, and climate change: How lifestyle inconsistency and do-gooder derogation impact decarbonization advocacy
Gregg Sparkman and Shahzeen Z. Attari (2020) *Energy Research & Social Science*, 59.

- Survey & Supplemental Information
- Data (xlxs)

Easy but not effective: Why "turning off the lights" remains a salient energy conserving behaviour in the United States
Daniel C. Lundberg, Janine A. Tang, and Shahzeen Z. Attari (2019) *Energy Research & Social Science*, 58.

- Survey

- Data (xlxs)

Simple interventions can correct misperceptions of home energy use
Tyler Marghetis, Shahzeen Z. Attari and David Landy (2019) *Nature Energy*, 4(10), 874-881.

- Survey, Survey Answers, & Supplemental Information
- Data (xlxs)
- Omar I. Asensio (2019) Correcting consumer misperceptions, *Nature Energy, News and Views*

WaterWorks Game
Team: Carissa Knox, Kelsey Hinton, Bronson Bast, Ian Ford, Shree Harsha Sridharamurthy, Brent Kievit-Kylar, Evan Spiegel, Studio Cypher, Mike Sellers and Shahzeen Z. Attari

Funded by the Indiana Water Resources Research Center (IWRRC), Workshop on Political Theory and Policy Analysis, & Indiana University Office of Sustainability. Feel free to use the game and code with attribution.