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Simple interventions can correct misperceptions of home energy use

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Public estimates of energy use suffer from severe biases. Failure to correct these may hinder efforts to conserve energy and undermine support for evidence-based policies. Here we present a randomized online experiment that showed that home energy perceptions can be improved. We tested two simple, potentially scalable interventions: providing numerical information (in watt-hours) about extremes of energy use and providing an explicit heuristic that addressed a common misperception. Both succeeded in improving numerical estimates of energy use, but in different ways. Numerical information about extremes primarily improved the use of the watt-hours response scale, while the heuristic improved underlying understanding of relative energy use. As a result, only the heuristic significantly benefitted judgements about energy-conserving behaviours. Because understanding of energy use also predicted self-reported energy-conservation behaviour, belief in climate change, and support for climate policies, targeting energy misperceptions may have the potential to shape individual behaviour and national policy support.

To mitigate effects of climate change[1], researchers have proposed a variety of approaches to decrease emissions and stabilize atmospheric carbon dioxide concentrations. Although policy-level interventions are needed, changing behaviour may be a complementary pathway to accomplishing stabilization goals[2]. One obstacle to the adoption of pro-environmental policies and actions is the widespread misperception of home energy use. Past work has found that the electricity used by home appliances is underestimated by roughly a factor of three [3], with small overestimates for low-energy-use activities and large underestimates for high-energy-use activities[3,4]. Because individuals' perception of the amount of electricity used by home appliances may guide their energy-saving behaviour[5–7], this misestimation could present an obstacle to decreasing personal energy use. Conversely, better estimates may improve energy conservation, as illustrated by the conservation benefits of in-home smart devices that give real-time feedback on energy use[8,9], although these technologies may be years away from becoming mainstream. Therefore, understanding why home energy-use estimates are distorted may inform interventions for how to improve them.

There are at least two psychological factors that may account for systematic errors in estimates of energy use[10,11]. First, individuals may hold beliefs (perhaps unarticulated) about appliances' energy use. These beliefs may be derived from a variety of cues[12], from general (for example, size) to energy specific (for example, labelling). When individuals have access to reliable cues such as in-home feedback from smart devices, their beliefs may be accurate. But if individuals use unreliable cues—and they often do[13,14]—then their beliefs may be distorted. Vacuums are louder than ovens, for instance, but ovens use far more energy in one hour; if someone relied only on sound, they may underestimate the ovens' energy use. Indeed, past work suggests that people rely on frequency of use[15] and physical size[13] to estimate energy use, leading them to believe that some common or large appliances use more energy than they actually do. By contrast, people underestimate the energy used by heat-generating appliances[3] (for example, clothes dryers, heaters), suggesting that they are ignoring heat-generation as a valid cue to energy use. Errors in an individual's estimates, therefore, may reflect systematic errors in their underlying and perhaps implicit understanding of energy use, including how much energy appliances use relative to other appliances.

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

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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 energy estimation but nevertheless help subsequent energy decisions.

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 values of energy use (horizontal axis) and estimates of energy use (vertical axis) on a logarithmic scale. A person with perfect estimates would be expected to have a slope of 1 (Fig. 1a,b, dotted black line). A person who overestimated low-energy-use appliances and underestimated high-energy-use appliances would be expected to have a slope between 0 and 1. Here, in the control condition, the mean estimate slope was 0.31, 95% CI [0.29, 0.33] (Fig. 1), which is comparable to past work (for example, 0.28 in ref. [1]). (For relations between sociodemographic measures and estimate slopes, see Supplementary Table 1.)

As described above, misestimation may reflect two sources of error: underlying understanding of the appliances' energy use and use of the response scale to express those beliefs. In general, for a single predictor (x) and a single outcome (y), the slope in a linear regression predicting y from x is given by:

$$b_x = \rho_{xy} \frac{\sigma_y}{\sigma_x} \tag{1}$$

In the context of energy estimation, therefore, slopes can be decomposed into (1) $\rho_{\text{actual,estimates}}$, the correlation between individuals' estimates and the actual energy-use values; and (2) $\sigma_{\text{estimates}}/\sigma_{\text{actual}}$, the ratio between the standard deviation of individuals' estimates and the standard deviation of the actual values. We used the first of these, ρ, to measure one aspect of individuals' underlying and perhaps implicit understanding of the appliances' energy use: their relative ordering of appliances by energy use. A correlation of 1 indicates a perfect understanding of the appliances' relative ordering, whereas values of less than 1 indicate an incorrect understanding. We used $\sigma_{\text{estimates}}/\sigma_{\text{actual}}$ to measure their use of the response scale; a systematic overestimation of small values and underestimation of large values would be expected to produce a ratio less than 1, with ratios closer to 0 indicating a more compressed use of the response scale. Calculating these measures for each individual revealed that, in the absence of any intervention, estimation errors were due both to errors in their underlying understanding of energy use ($M_\rho = 0.54$, 95% CI [0.52, 0.56]) and to a compressed use of the response scale ($M_{\sigma y/\sigma x} = 0.56$, 95% CI [0.54, 0.58]).

We next investigated the interventions' causal impacts on energy estimation (including estimate slopes, understanding of relative ordering and the use of the response scale to report that understanding) by using multiple regression and controlling for a range of sociodemographic measures (see Supplementary Table 1). Compared to the control condition ($M = 0.31$), both interventions improved estimate slopes (explicit heuristic: $M = 0.36$, 95% CI [0.34, 0.38]; effect of heuristic on estimate slope: $b_{\text{heuristic}} = 0.05 \pm 0.01$ s.e.m., $P < 0.001$; scale-use information: $M = 0.44$, 95% CI [0.42, 0.46]; effect of scale-use information on estimate slope: $b_{\text{scale-use}} = 0.13 \pm 0.0$ s.e.m., $P < 0.001$), although scale-use information had more than double the impact of the heuristic. The interventions were additive (interaction between interventions: $|b| < 0.01$, $P > 0.80$); participants who received both interventions had the best estimate slopes ($M = 0.48$, 95% CI [0.47, 0.50]).

Although both interventions improved energy estimate slopes, they accomplished this by improving different aspects of the estimation process (Fig. 1). The scale-use intervention caused a small but statistically significant improvement in understanding of the appliances' relative energy use ($M_\rho = 0.56$, 95% CI [0.54, 0.58]; effect of scale-use information on relative ordering: $b_{\text{scale-use}} = 0.02 \pm 0.01$ s.e.m., $P = 0.03$), but most of its effect on estimate slopes was driven by an improved use of the response scale ($M_{\sigma y/\sigma x} = 0.77$, 95% CI [0.75, 0.79]; effect of scale-use information on scale use: $b_{\text{scale-use}} = 0.21 \pm 0.02$ s.e.m., $P < 0.01$). The scale-use intervention decreased estimates for appliances that use little energy while increasing estimates for appliances that use a lot. This systemic improvement depended on supplying information about both ends of the response scale; Supplementary Fig. 2 illustrates that supplying information about just one extreme of the response scale (at the high end) increases estimates overall without decreasing the overestimation of energy use in low-use appliances, as found in past work[22].

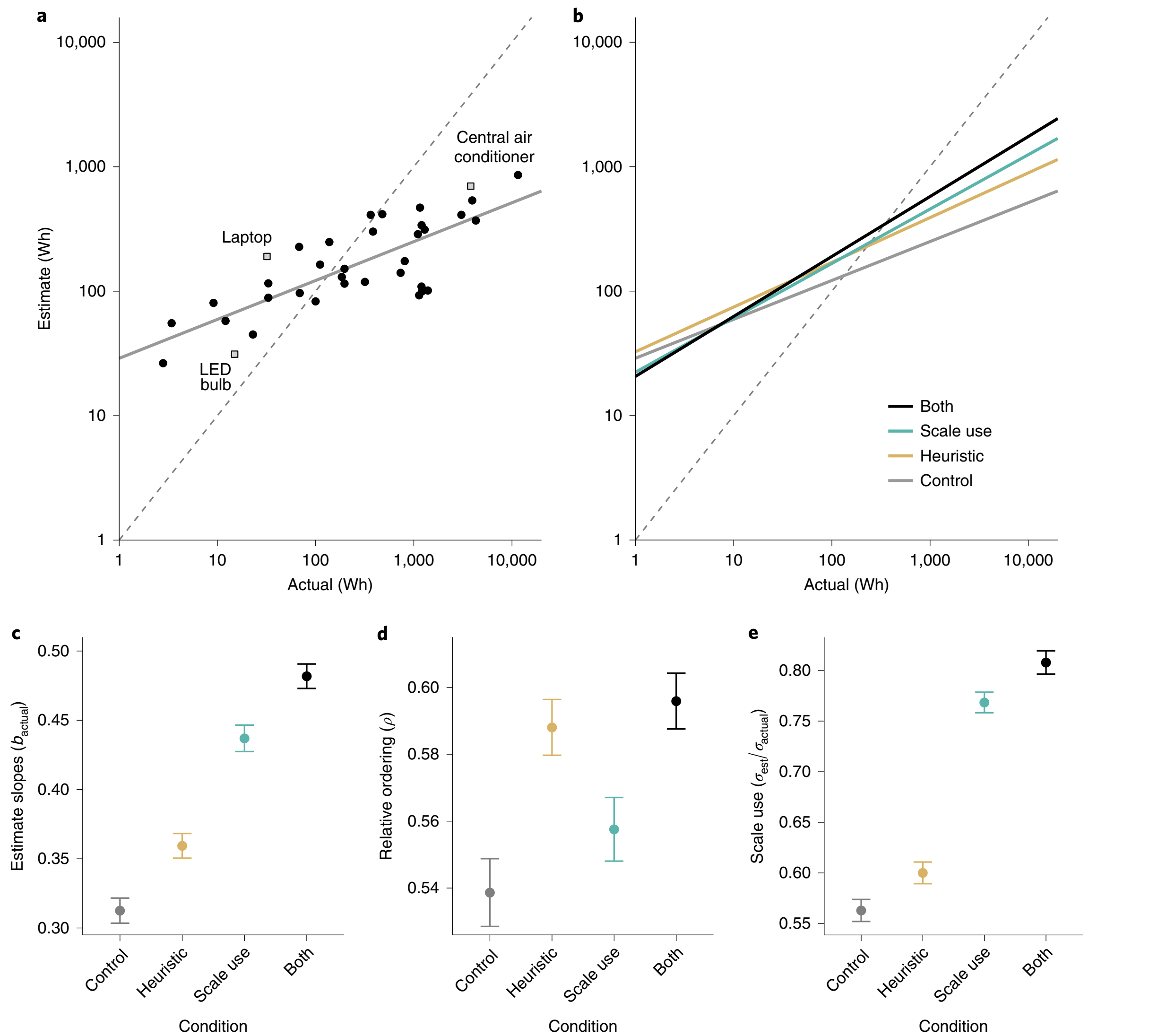

Fig. 1 | Relation between actual and estimated energy use. a, Energy estimates in the control condition for 36 home appliances ($n=410$). The solid grey line indicates the relation between actual and estimated energy use (on a log-scale). The dashed line illustrates perfect estimation performance: a 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.

Because an individual's estimate slope was the product of our measures of relative ordering (ρ) and scale use ($\sigma_{estimates}/\sigma_{actual}$), we can translate these effects into relative impacts on estimation slopes by dividing by the mean estimation slope in the control condition. For the scale-use intervention, its effect on scale use accounted for an increase of 38% in estimation slopes (that is, 0.21/0.56), while its effect on understanding of the appliances' relative ordering accounted for an increase of only 4%.

By contrast, although the explicit heuristic also had a significant impact on the use of the response scale ($M_{\sigma y/\sigma x}=0.60$, 95% CI [0.58, 0.62]; effect of heuristic on scale use: $b_{heuristic}=0.04\pm0.02$ s.e.m., $P=0.02$), more of its impact was driven by improvements in understanding of the appliances' relative energy use ($M_{\rho}=0.59$, 95% CI [0.57, 0.60]; effect of heuristic on relative ordering: $b_{heuristic}=0.05\pm0.01$ s.e.m., $P<0.01$). Again, we translated these effects into relative impacts on estimation skill: the heuristic's effect on scale use accounted for an increase of 7% in estimate slopes (that is, 0.04/0.56), while its effect on understanding of the appliances' relative ordering accounted for an increase of 9%. Therefore, although the explicit heuristic's impact on estimate slopes was more modest than the impact of the scale-use intervention (Fig. 1c), its impact was driven more by an improved understanding of the appliances' relative energy use (Fig. 1d)—an improvement that was more than twice as large as the improvement due to the scale-use intervention. A direct comparison of the two interventions revealed that relative ordering was significantly better after the explicit heuristic intervention than after the scale-use intervention ($t_{814}=2.41$, $P=0.016$, Student's t-test), while scale use was significantly better after the scale-use intervention than after the explicit heuristic intervention ($t_{814}=11.4$, $P<.001$). (See Supplementary Tables 2 and 3 for full results of the regression analyses of relative energy use and scale use.)

For each appliance, the mean post-intervention estimates were compared to the control condition (that is, $M_{intervention}/M_{control}$) (Fig. 2). Using a mixed-effects model of energy estimates, we found that,

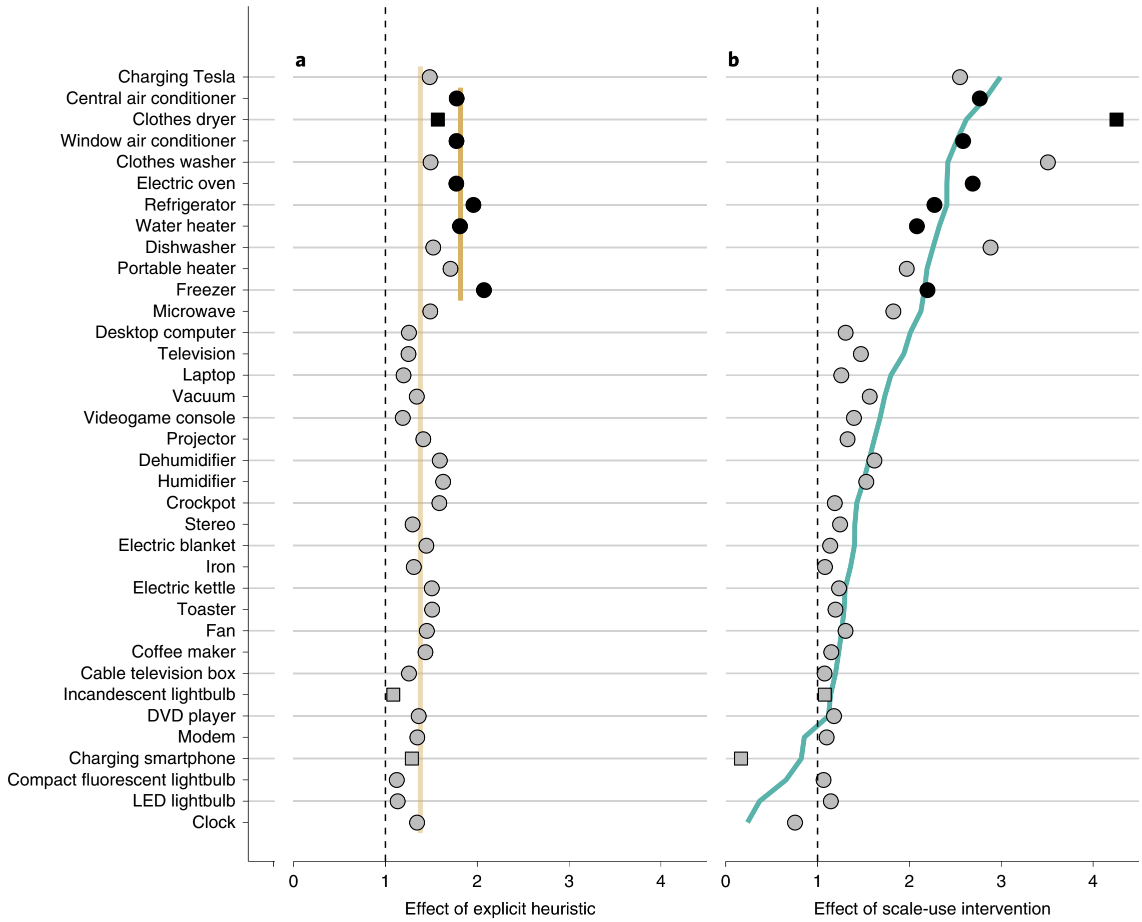

Fig. 2 | Effects of explicit heuristic and scale-use information interventions on energy-use estimates of home appliances. a,**b**, Comparison of mean post-intervention estimates to mean control estimates ($n=410$) for each appliance for the explicit heuristic (**a**, $n=406$) and scale-use (**b**, $n=411$) 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.

as predicted, the heuristic had a targeted impact on estimates for large appliances that heat or cool (Fig. 2; targeted impact of heuristic: $b=0.26\pm0.1$ s.e.m., $P=0.02$; targeted impact of scale-use information: $b=0.17\pm0.1$ s.e.m., $P=0.13$; difference between interventions: $b=-0.09\pm0.11$ s.e.m., $P=0.42$), suggesting that the heuristic improved participants' underlying understanding of those specific appliances. By contrast, the impact of the scale-use intervention was systematically related to how much energy people thought the appliance used (scale-use intervention: $b=0.12\pm0.0$ s.e.m., $P<0.01$; heuristic: $b=0.00\pm0.01$ s.e.m., $P=0.88$; difference between interventions: $b=-0.11\pm0.01$ s.e.m., $P<0.001$), with larger increases in estimates for appliances thought to use more energy and no increases or even decreases for low-usage appliances (Fig. 2). This pattern follows naturally from our model, which predicts that explicit information about appliances' energy use may help recalibrate the way an individual transforms their underlying understanding into numerical responses in watt-hours.

Effects of interventions on behavioural choice

To investigate whether our interventions may also have downstream benefits for behaviour, we evaluated the participants' ability to identify notable energy-saving behaviours, a potential precursor to successful behaviour change[26]. We presented participants with pairs of behavioural changes or activities, and they had to decide which option would lead to greater energy savings (for example, line-drying rather than using a clothes dryer, versus reading a book rather than watching 20 h of television). These pairwise dilemmas involved appliances for which participants had supplied energy-use estimates. Accuracy in the control condition was poor ($M=0.60\pm0.01$ s.e.m.). Participants were more accurate when their previous energy estimates for relevant appliances more clearly distinguished the correct alternative (that is, a larger ratio between estimates for the two activities in question; $\beta=0.12\pm0.05$ s.e.m., $P=0.01$), and they were generally more accurate if they had a better overall understanding of appliances' relative ordering by energy use (that is, ρ; $\beta=0.19\pm0.02$ s.e.m., $P<0.01$; Fig. 3a); these results suggested that individuals used their underlying understanding of energy use both for quantitative estimates of energy use and when deciding between conservation behaviours. (See Supplementary Table 5.)

Our psychological account predicts that the explicit heuristic should also improve individuals' ability to evaluate energy-saving behaviours because it targets their underlying understanding of energy use, whereas information about the extremes of the response scale should only improve their ability to generate numerical estimates. Indeed, the heuristic significantly improved the ability to choose between energy-saving behaviours (effect of heuristic on

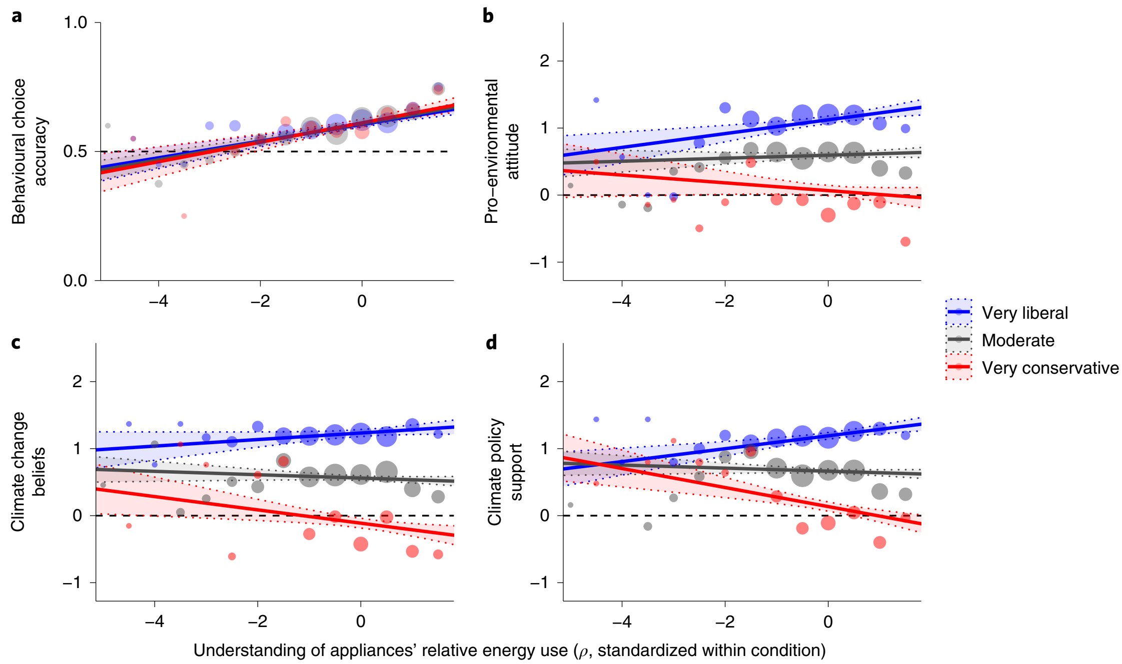

Fig. 3 | Individual differences in understanding the appliances' relative energy use. a–d, Relations between understanding the appliances' relative energy use and behavioural choice accuracy (**a**), pro-environmental attitudes (**b**), climate change beliefs (**c**) and climate policy support (**d**), 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 used more energy ($b=0.15\pm0.07$ s.e.m., $P=0.03$; see Supplementary Table 7), increasing the odds of success by 16%. For the remaining dilemmas, which included scenarios where the heuristic was irrelevant or even misleading (that is, where the less-helpful behavioural change involved a temperature-changing appliance), the heuristic's effect was marginally greater than 0 ($b=0.09\pm0.05$ s.e.m., $P=0.07$), perhaps because the heuristic prompted reflection more generally on appliances' features that meaningfully affect energy use. Finally, the explicit heuristic's benefit for behavioural choices was completely mediated by its effect on understanding of energy use (see Supplementary Note 4 and Table 8).

Individual differences in understanding relative energy use

The ability of the participants to estimate the appliances' energy use varied, even after accounting for differences due to the interventions. We estimated the endogenous variability in the participants' understanding of the appliances' relative ordering by energy use (that is, ρ) and their use of the response scale (that is, $\sigma_{\text{estimates}}/\sigma_{\text{actual}}$) by standardizing these two measures within each intervention condition. Individual differences in the use of the response scale had a negligible relation to owning an Energy Star-rated refrigerator ($b=-0.03\pm0.06$ s.e.m., $P=0.67$) or adopting energy-efficient lightbulbs ($b=0.04\pm0.05$ s.e.m., $P=0.45$), and using more of the watt-hours response scale was actually associated with reporting longer showers ($b=0.62\pm0.15$ s.e.m., $P<0.01$), perhaps reflecting 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 energy estimations and behavioural choices both draw on an underlying understanding of the appliances' energy use. (See Supplementary Table 4.)

Finally, we found that better understanding of the appliances' relative energy use also predicted stronger pro-environmental attitudes, climate change beliefs and support for climate policy, but only at the liberal end of the political spectrum (Fig. 3). Better understanding of relative energy use predicted pro-environmental attitudes and beliefs among very liberal participants (pro-environmental attitudes: $\beta=0.10\pm0.03$ s.e.m., $P<0.01$; climate change belief: $\beta=0.05\pm0.03$ s.e.m., $P=0.06$; climate policy support: $\beta=0.10\pm0.02$ s.e.m., $P<0.01$). However, the strength of these relationships decreased significantly for more conservative participants (interaction with political ideology, which ranged from 0 (very liberal) to 6 (very conservative): $-0.04\le b\le-0.02$, $P<.01$), so that, among very conservative participants, Better understanding of the appliances' relative energy use actually had a negative relation with climate change belief and policy support (Fig. 3), which is in line with past findings that knowledge may increase ideological polarization[27]. (See Supplementary Table 9.)

Discussion

The current study identified two approaches to improving lay estimations of home energy use: supplying information about the use of the response scale and supplying an explicit heuristic. Although the effect of scale-use information on estimation skill was nearly five times greater than the effect of the explicit heuristic, only the heuristic caused a statistically significant improvement in downstream energy-conserving behavioural choices. This result illustrates one of the core assumptions of our psychological account: quantitative energy estimations reflect both individuals' underlying understanding of energy use and the processes by which they transform that understanding into numerical responses along some response scale. Thus, when it comes to improving home energy estimation and conservation, care must be taken to develop interventions that benefit underlying understanding, not just use of the response scale. Similar considerations apply to the interpretation of quantitative estimations more broadly. For many socially and politically relevant domains (for example, immigration), errors in estimates have been taken as direct evidence of underlying bias, without accounting for distortions introduced by misuse of the response scale[19].

The 'explicit heuristic' approach to interventions attempts to improve downstream conservation behaviour by offering simple, explicit guiding rules that change the upstream understanding of energy use. We thus add another approach to the existing classes of interventions that target energy conservation[28]. For example, framing interventions have found that environment- and health-based messaging outperforms information about monetary savings for energy conservation[29]. Another class of successful interventions uses social norms to motivate home energy conservation[30]. Here we show the potential power of using a simple heuristic to improve people's underlying understanding of energy use—in particular, their understanding of the appliances' relative energy use. We also illustrate the pitfalls of trying to improve energy estimates without considering the underlying mechanism: While the scale-use intervention improved estimates of energy use, it had a negligible effect on decisions, which is in line with other work on numerical anchors[23].

Our account focusses on how individuals use a quantitative response scale to express their understanding of energy use, but there are certainly other processes involved in their estimation of energy use. For instance, individuals' estimates have been shown to incorporate salient but unreliable features of their experience[12], such as appliances' size or the frequency with which they are used[13,15]. Similarly, individuals may use a salient numerical anchor to generate a first-pass estimate and then adjust it upward or downward[31] (Supplementary Fig. 1). Future work could incorporate these and other processes into the model, thus further distinguishing errors in estimates that are due to underlying misperceptions of energy use from those that are artifacts of the process of generating explicit estimates along some numerical response scale.

We found that better understanding of a very local energy context (home electricity use) predicted attitudes and beliefs about phenomena on a far larger scale (for example, climate policy). The nature of this relation varied systematically with political ideology, so that belief polarization increased with estimation skill. This relation mirrors a pattern found elsewhere, in which knowledge increases polarization for politically partisan issues[27]; more formal education, for instance, is associated with greater concern about climate change among liberals, but with less concern among conservatives[32,33]. One explanation of this finding is that individuals engage in 'motivated reasoning,' selectively using their knowledge to reinforce beliefs that align with their cultural or political identities[32,34]. To overcome motivated reasoning, interventions targeting estimation skill or other aspects of energy literacy may need to incorporate ways for participants to 'save face' as they change their minds on partisan issues.

Future work is required to develop and test new explicit heuristics that target other widespread distortions in public understanding of energy use, such as overestimating the energy used by appliances that are physically large or used frequently[13,15]; that target effective behaviours, such as adopting energy-efficient appliances[2,5]; or that target basic principles and 'folk theories' of how appliances work and use energy, which are often fundamentally wrong[35,36]. Moreover, further research is required to determine how best to disseminate such heuristics, although one possibility is through appliance labelling in a manner similar to nutritional labelling[37].

In principle, energy-conservation behaviour may be improved by a variety of means, including but not limited to top-down policies, market-based incentives, extensive educational programmes, home energy audits and new home technologies. For instance, in-home smart devices with real-time feedback on energy use may encourage energy conservation[8,9], potentially lessening the consequences of energy-use misperception. However, implementing effective climate policies has been politically difficult[38,39], home audits require time and resources that can prohibit scaling up, and new in-home energy technologies may be years away from becoming mainstream. The current study suggests that simple explicit heuristics may improve perceptions rapidly and cheaply. Widespread and lasting behavioural change, therefore, might be encouraged by introducing informative heuristics that are both memorable and easily spread within the ecosystem of ideas.

Methods

Participants. Adults ($N = 1,645$) were recruited online via Amazon's Mechanical Turk on 24 and 25 April 2018. The target sample size was determined from past work[3]. Participants were compensated US$2 for their participation. The sample was 49.3% male with a median age of 34 years and a median household income of US$40,000 to US$80,000, and 58% held a bachelor's degree or higher (compared to the United States population, which in 2016 was 49.2% male, had a median age of 37.7 years and a median income of US$55,322, and 46% had some college coursework or an associate's degree or higher[40]). Fifty-four percent self-identified as liberals, 19% as moderates and 27% as conservatives (skewing liberal compared to 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, 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 than 1 day (1,532 min).

Ethics statement. This research was approved by Indiana University's Internal Review Board at the Office of Research Administration, and informed consent was received from all participants.

Constraints on generalizability. The demographic and political ideology measures for our sample indicate some selection or response bias relative to the US population. This bias may place constraints on the generalizability of our findings, although three considerations point to their robustness.

First, past work has found that Mechanical Turk participants were slightly more demographically diverse than those represented in standard internet-based samples, and they were significantly more diverse than the typical sample of college-educated Americans[48]. Indeed, although our sample was not representative of the US population in education or political orientation, it did include participants from across the ideological spectrum and from a range of different educational backgrounds.

Second, we were able to leverage our sample's demographic and ideological diversity by incorporating sociodemographic measures into our analyses. The reported effects were thus adjusted for all sociodemographic measures. These adjustments allowed us to estimate how demographic variables and political orientation related to our dependent measures and how they interacted with our experimental interventions.

Third, initial pilot studies confirmed our primary findings in samples from a different population: volunteer undergraduate students at an American research university. These small samples confirmed the differential effects of using two types of interventions on energy estimation (see Supplementary Information).

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

All data generated or analyzed during this study are available online: https://osf.io/2qbxt/

Code availability

The code to generate figures and results is available upon request.

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Author contribution

S.Z.A. and D.L. designed the research. S.Z.A collected the data. T.M. analyzed the data. T.M., S.Z.A. and D.L. wrote the paper.

Competing interests

The authors declare no competing interests.

Additional information

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Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	We used Qualtrics, a web-based service for building surveys and collecting data online. Online subject recruitment used Mechanical Turk, a labor market run by Amazon.
Data analysis	All analyses were conducted in the R statistical computing environment.

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Behavioural & social sciences study design

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Study description	Quantitative experimental
Research sample	Adults (N = 1645) were recruited online via Amazon's Mechanical Turk between April 24th and 25th 2017. The sample was 49.3% male, with a median age of 34 years, a median household income of $40,000–$80,000, and 58% with a college degree or more (compared to 49.2% male, median age of 37.7 years, median income of $55,322, and 46% with some college or an associate's degree or more in the U.S. in 2016). Fifty-four percent self-identified as liberals, 19% as moderates, and 27% as conservatives (skewing liberal compared to the US population).
Sampling strategy	Random assignment to condition. A target sample size of N = 1600 was determined from past work (Attari et al, 2010, PNAS).
Data collection	Participants completed the study online on a computer.
Timing	Between April 24th and 25th 2017, inclusive.
Data exclusions	One participant was removed from the analysis of shower length for reporting a typical shower length of longer than one day (1532 minutes). This was not pre-established.
Non-participation	Participants self-selected to participate online. We cannot know how many potential participants viewed the online recruitment but chose not to respond.
Randomization	Condition was randomized.

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☒	☐	Animals and other organisms
☐	☒	Human research participants
☒	☐	Clinical data

Methods

n/a	Involved in the study	
☒	☐	ChIP-seq
☒	☐	Flow cytometry
☒	☐	MRI-based neuroimaging

Human research participants

Policy information about studies involving human research participants

Population characteristics	See above.
Recruitment	Participants were recruited online via Amazon's Mechanical Turk. This limits the sample to adults who have access to a computer and to the internet. Past work using this recruitment strategy has found results that are similar to those found using in-person procedures. We do not know of any reason to suspect that computer ownership is likely to impact results. In the Methods, we compare our sample to the US population, and report some biases: our sample is more educated and more liberal than the adult US population. Analyses accounted for all sociodemographic measures.
Ethics oversight	Indiana University IRB

Note that full information on the approval of the study protocol must also be provided in the manuscript.