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Better rules for judging joules: Exploring how experts make decisions about household energy use

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ABSTRACT

Public understanding of home energy use is rife with biases and misunderstandings that can stymie the adoption of efficient technologies and conservation practices. Studying how energy experts make energy-related judgments can help design decision support tools to correct misperceptions held by novices. Here we conduct interviews with electrical engineers (n = 10), physicists (n = 10), and energy analysts (n = 10) to document expert judgments about energy use and to identify their cognitive shortcuts (heuristics) for household energy decision making. Performance on an energy estimation task confirmed that energy experts have more accurate estimates of home energy use than novices. We document 24 unique expert heuristics related to device functions, components, and observable cues used by experts while making energy-use judgments. A follow-up survey with the experts indicated that these expert heuristics are generally more accurate than novice heuristics. The library of heuristics created in this study can be useful additions to education programs designed to improve public energy literacy and decision making.

1. Introduction

Residential end-use accounted for 38% of electricity sales in the United States in 2019 [1]. Efforts to mitigate climate change, among other causes, stand to substantially benefit from curbing electricity use through greater uptake of efficiency and conservation measures at the household level [2,3]. However, productive engagement with the public about household energy use is complicated by challenges related to misperceptions of effective ways to conserve energy in our lives.

Public understanding of energy use is rife with systematic and problematic biases. Commonly, people do not know the difference between energy and power [4] and do not know what are the most effective changes they can make to decrease their household energy use. For example, when asked what is the single most effective thing they can do to decrease energy use, participants' modal response has been "turning off the light" since the 1980s [5–7]. Although turning off the light is easy to remember, it is not the most effective action one can take to decrease their energy footprint [2]. Turning off the lights exemplifies the stark differences between public or "folk" understanding and expert analysis of effective ways of conserving energy use [2].

Although there are many tools that exist to teach people about what are effective energy conservation strategies, they come with varying degrees of difficulty in accessibility and use. For example, there are high search costs associated with finding an efficient home or efficient appliances [8]. Programs like Energy Star use simple decision architecture (employing effective ways of presenting information and choices) [9,10] to identify the most efficient appliances in class leads consumers to save energy and money. A complementary approach to improving public understanding of energy use lies in correcting the perceptions and mental models people use to make decisions about energy, and testing whether that leads to energy savings.

One key element of decision making is the use of heuristics, simple rules and principles used to make judgments without deliberate and elaborate analytical reasoning [11]. While heuristic processes can often yield valid, "good enough" results [12], they can also lead to biased assessments [13]. (These competing perspectives on heuristics are sometimes referenced as the "heuristics-and-biases" paradigm associated with bounded rationality versus the "fast-and-frugal" paradigm highlighting the adaptive nature of heuristic use [14].) Aiding cognitive efficiency, heuristics guide our attention, serving to sort cues and distinguish between critical and non-critical information.

When it comes to novice energy perceptions (i.e., how people

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without professional experience or expertise with energy understand the topic of energy use), people tend to pay attention to cues that may not be indicative of the amount of work being done or energy being used by the device. Past research found that undergraduate participants grouped appliances based on functionality and size but not in terms of energy use; some large appliances were perceived to use more energy even though actual energy use was low [15]. Other work indicates that size is a primary driver of novice energy estimates [16] and that the frequency with which people interact with the device is used as a cue to indicate how much energy it uses [17].

To create a comprehensive catalogue of novice energy heuristics, van den Broek and Walker [18] asked undergraduate participants to work in groups to rank order the energy use of items on a list of household appliances. Through thematic analysis of these group discussions, nine heuristic themes and 24 separate heuristics were identified. The most common heuristic themes related to comparisons between devices (e.g., devices with related functions use similar amounts of energy, as in DVDs players and televisions), the time-based aspects of device use (e.g., the faster a device completes a task, the more total energy it uses), as in a rapid-boil kettle, and the physical features of devices (e.g., the number of components a device contains, as in a computer with added drives and ports). In terms of individual heuristics, the most frequently observed heuristics focused on duration of use, device category, and heat production. Subsequently the authors incorporated one of the more frequently evoked heuristics, "a good way to estimate how much energy a household device uses is to think about how much heat it produces", into educational materials, and was shown to improve performance by a new study group on an energy-use rank-ordering task [18].

Folk cues like frequency of use can lead to inaccurate estimates of energy use [17]. In addition to inaccurate estimates, people also have incorrect theories for how basic energy systems work. For example, people commonly use valve-theory to explain how thermostats work, i.e., the thermostat controls the amount of heat, rather than feedback theory where the thermostat senses the temperature and turns the furnace on or off to maintain a given temperature [19].

We use the term *cultural heuristic* to indicate decision rules that are salient in our culture but may not be the best or most accurate rules to follow. "Turning off the lights" is a sticky and salient heuristic and is a good example of an inaccurate cultural heuristic for the most effective action to decrease energy use. Cultural heuristics are different from *natural heuristics* such as anchoring and insufficient adjustment [13], which are a function of the way our mind understands and interprets data (psychophysics).

Cultural heuristics are also distinct from *expert heuristics*, which are rules that experts use to distinguish between relevant and irrelevant information and to navigate difficult decision landscapes. Subject-matter experts distinguish themselves from novices by virtue of skills acquired from collecting subject-specific knowledge and practices over the course of many years of academic and professional experience [20–22]. Experts develop a range of cognitive benefits and capacities that improve performance on relevant tasks [23], including more accurate mental representations of domain-specific tasks and protocols [24] and better problem-solving strategies and strategy selection processes [25]. Thus within the domain of energy, an expert would be considered a person with extensive educational and professional experience with energy and energy-adjacent subjects.

Across a wide variety of domains, differences in judgments and behaviors between experts and novices often stem from differences in perception. In many cases, these differences in perception themselves turn on the expert's deployment of categorical thinking that capture important domain-relevant principles. Novice judgments are instead often driven by surface similarities and potentially irrelevant relationships or cues [24,26,27]. We posit that novice energy estimators are often misled by surface similarities and simplistic heuristics in making energy estimates, while experts are guided by deeper, more principle-based causal explanations. Hence, it can be expected that expert heuristics, acquired, tested, and used over years of experience, would be more accurate and effective than novice heuristics in making energy-related judgments. An example of an expert heuristic in the energy space is "large appliances that primarily heat or cool things use a lot more energy than people think" [28]. Participants who were provided this expert heuristic did better than the control condition in estimating actual energy use by appliances [28].

It is important to note here that heuristics of all types by their very nature are cognitive shortcuts that help people navigate complex decision making or judgment tasks. Even expert heuristics can lead to errors in judgment. For the example above, there are some large appliances that heat or cool but use relatively little energy compared to appliances that do not (e.g., a refrigerator – a large appliance that cools – is rated at ~ 360 W whereas a vacuum cleaner – a smaller appliance that sucks air – is rated at ~ 800 W). Although heuristics are not perfectly applicable in every situation, thoughtfully developed heuristics can balance simplicity (easy of use) and performance (they improve judgment accuracy) such that their overall impact is to improve decision making.

All expertise is not the same. An important component of the domain of energy use is the heterogeneity of relevant expertise: some experts build and repair actual devices (electrical engineers), others (physicists) deal with electricity and magnetism as general phenomena, still others (energy analysts or technical subject matter experts) must combine understandings of electrical devices and their principles with an understanding of usage in context. Thus, to catalog potentially useful expert heuristics, it is critical to investigate the knowledge and decision processes of multiple expert groups, as different experts may focus on different features of energy and energy use.

Here we aim to create a library of expert energy heuristics for the home and aim to answer three research questions: (1) Do experts in energy-related fields have more accurate estimates of home energy use than novices? (2) If so, what are some of the heuristics they use to make their energy estimates quickly without using back-of-envelope calculations or basic memory recall? (3) How accurate do the experts find their own heuristics relative to those associated with novices?

2. Methods

2.1. Recruitment

Expertise relevant to the domain of home energy use can be quite diverse, and defining expertise is not an exact science. Some people might deal with electricity and magnetism as a general, conceptual phenomenon. Others design electrical devices, while still others combine technical knowledge of devices with an understanding of actual usage in the home. To cover each of these three prospective types of energy-relevant expertise, ten experts each were recruited from three professional categories: electrical engineers, physicists, and energy analysts.

Markers of expertise include degree of education and amount of experience [20,29]. Experts in the electrical engineering and physics were recruited from their respective academic departments of several colleges and universities located in the American Midwest and Southeast. Each of these experts held a PhD in their field of expertise and 19 out of 20 were tenured professors. Of the 20 experts in these two groups, the amount of professional (post-education) experience ranged from 8 to 53 years, with a mean length of professional experience of 29 years.

Experts qualified as an energy analyst when their major professional activity focused on energy use in the home. Energy analysts were identified through web searches and the authors' knowledge of the field. Energy analysts worked in research institutions, energy non-profits, energy consultancies, and other private-sector groups. As a group, energy analysts had 10 to 48 years of professional experience (mean 24 years), and all 10 experts held graduate degrees.

Only three of the 30 experts in our sample were female, and the average age of our participants was 54 years.

To gain a better understanding of how the participant viewed their own expertise, we asked participants to describe whether they thought their expertise in their field was relevant for estimating energy use of home appliances. Experts rated the relevance of their expertise on a Likert scale ranging from 1 ("not at all relevant") to 7 ("highly relevant"). Among electrical engineers, 40% rated their expertise as "somewhat relevant" and 30% rated their expertise as "mostly relevant." Among physicists, 30% rated their expertise as "somewhat relevant" and 20% rated their expertise as "mostly relevant." Among energy analysts, 40% rated their expertise as "somewhat relevant" and 30% rated their expertise as "mostly relevant." No expert deemed their expertise to be "highly relevant" to the task of estimating appliance energy use.

Our experts also addressed how often they engage with members of the general public on issues related to personal energy use. For this question, 20% of electrical engineers, 0% of physicists, and 50% of energy analysts reported speaking to the public monthly, weekly, or daily.

Finally, 3% of our sample had a professional engineer certification, 10% had received training as an electrician, and none was certified to conduct home energy audits.

Across all groups, participants were recruited via email. Prospective recruits received at least one follow-up email message and some received follow-up visitations at their publicly listed office. All participants were offered $20 for their participation. Of all participants, 57% accepted this payment. Our total sample is 30 participants. The sample size of our study was not based on the saturation of ideas but rather for an exploratory study to extract and build a first of its kind "heuristics library" for home energy use. Henceforth, we refer to our participants as experts.

2.2. Procedure

Data on expert thinking was collected between March 2019 and August of 2019. Where possible, interviews were conducted in person. When distance or other constraints made in-person interviews not feasible (for 15 experts), interviews were conducted over the phone or via video chat, with quantitative data being collected through an online survey platform.

Each session had two principal components: first a choice task and second an appliance estimation task. (This order reverses the presentation of items in previous work [28].) Experts were also asked a series of questions about energy use in their personal and professional lives as well as a set of questions about their background and field of expertise.

Qualitative data was coded and analyzed using NVivo (v12) and quantitative data was analyzed using R (v3.5.2). Analysis of variance was used to assess differences in performance between expert categories. T-tests were conducted to assess the performance of experts and their heuristics relative to previously established novice baselines [18,28]. Pearson's correlation coefficient was used to assess the relationship between measures of expert performance and data about the experts themselves. For all statistical analyses, a p-value of 0.05 was used as the threshold for significance.

2.2.1. Choice task

In the choice task, experts were presented with nine sets of two or three common household devices. For example, one set was a choice between a window air conditioning unit and an electric oven. For each set, experts were asked to state which of the presented devices would use less energy than the other(s) given that all devices were run for the same length of time. In total, 24 devices were used across the nine choice tasks, covering the major categories of domestic electricity use: heating and cooling, water heating, small and large appliances, lighting, and electronics.

The choice task was paired with protocol analysis, wherein research participants are asked to think aloud as they perform a task, thereby providing instantaneous and unfiltered insight into the cognition associated with completing the task [30]. In this case, experts were asked to verbalize their thinking and thought processes to the best of their abilities while they selected the device that used the least energy in each choice set. Experts were given practice exercises to accustom them to thinking aloud [30]. When, in the middle of a given choice task set, an expert spent a moderate amount of time without speaking, they were given a gentle prompt to continue vocalizing their thoughts.

2.2.2. Appliance estimation

Following the choice task, experts were asked to provide their estimates of the energy use of 17 household devices. To provide a concrete reference point for quantifying their judgments about energy use, experts were told: "A standard incandescent light bulb uses about 100 units of energy in one hour. When you are asked to estimate units of energy, please compare each appliance to this light bulb. Think about whether each appliance below uses less energy or more energy than this light bulb. Please use this number to help you make your estimates." (The term "unit" was used rather than the more technical Watt-hour to be consistent with previous research on energy estimation by the general public, which tends to be less fluent with units of energy.) Based on these instructions, experts were then asked to estimate the units of energy used by these 17 devices when they are in use for one hour. To compare expert performance with that of energy "novices," we examined the baseline data of the estimation task in previous work [28].

Data collection ended with a set of questions to collect information about the experts' sense of numeracy (drawing two items from the Subjective Numeracy Scale [31]), educational and professional backgrounds, perception of the applicability of their expertise to assessing energy use, and demographic profile.

2.3. Coding the choice task

To extract the list of heuristics employed by experts during the choice task, the verbal reports made by the experts were transcribed and analyzed. The first layer of analysis entailed developing a coding scheme to categorize the content of the verbal reports. A codebook was developed to sort the information used by the experts into primary and secondary categories. Primary codes were developed for the three general content areas of the expert interviews: references to (1) observable cues about energy use, (2) device functions, and (3) device components. (A fourth primary category was created to catch comments that did not fall in the areas of the main primary categories.) Each primary code was disaggregated into several secondary codes, each of which refers to a more detailed aspect of the primary code's general theme. For example, the "Observable Cues" primary code family contained eight secondary codes, including "hot to touch," "dims lights/trips circuits," and "thick cord."

This codebook was drafted by a single researcher then modified based on four rounds of independent coding by two coders. Each round involved two coders using the codebook to code a single, randomly selected interview transcript. Following the first two rounds of coding, qualitative discussions of differences between the two coders guided revisions to the codebook. After the third and fourth rounds of coding, unweighted Cohen's kappa (κ) values were calculated to quantify intercoder agreement [32]. These values were 0.83 and 0.85, respectively, which are generally considered to indicate fairly strong agreement [33]. Following these four rounds of codebook revision, a final version of the codebook was established. (See Supplementary Table 1.)

Two further rounds of joint coding were performed to assess whether there was sufficient agreement between two coders to justify using a single coder for the entirety of the interview data. In each round, three randomly selected interviews – one from each expert group – were independently coded by two coders. The threshold of $\kappa = 0.8$ was understood as sufficient for single coding [33]. The κ value for intercoder agreement level for the first round of coding was 0.94. A second round of coding with the same codebook and three new transcripts was completed to confirm acceptable intercoder reliability had been achieved and was replicable (κ = 0.80). Based on the high level of intercoder reliability, a single coder was used to code all the remaining interviews.

After the expert interviews were coded according to the list of secondary codes, a second layer of analysis extracted a set of heuristics from the secondary codes. This extraction was performed by a single researcher. In this process, all pieces of text with a given secondary code were first read for whether they stated a rule related to energy use and then assessed for thematic similarities across the texts. In each secondary code group, coded quotes were sorted into collections that describe a similar rule.

The secondary code "hot to touch," for example, was applied 28 times across 19 separate experts. As these 28 excerpts were read, they were grouped together when they expressed similar ideas. Within "hot to touch," the following quotes were two among several that were seen as conveying the same idea: "I know that the light bulbs in the digital projector are pretty intense and they can be, they're very hot, so you're drawing quite a bit of power." (Physicist #9) and "… I know that the XBox that my son used tends to be warm. Warm tends to tell me it's using energy." (Energy Analyst #8). After reviewing the set of these case-specific statements, the generalized heuristic: "Devices that become hot to the touch use more energy than similar devices that do not" was extracted.

For each thematically similar cluster of quotes, a heuristic was extracted and defined such that it articulated a general form of the ideas expressed by the experts. The result was a list of 24 unique heuristics (see Table 1 below).

Table 1
Heuristics extracted from the choice task, classification of heuristics, their use by experts, and expert assessment of their accuracy. Note that expert heuristics have been classified into types, whereas novice heuristics have not (blank in column 2).

(1) Heuristic	(2) Type	(3) Number of experts who used the heuristic at least once (conditional probability in parenthesis: when the heuristic is used, does the expert choose the correct answer)			(4) Expert assessment of heuristic accuracy (N = 16) (1 = mostly inaccurate, 4 = mostly accurate)
		Electrical Engineers (n = 10)	Physicists (n = 10)	Energy Analysts (n = 10)	Mean (SE)
A greater temperature change requires more energy than a smaller temperature change	Function	3 (50%)	4 (60%)	1 (100%)	3.9 (0.06)
Insulation helps to reduce the energy use of devices that heat and cool	Component	0 (–)	4 (67%)	3 (50%)	3.8 (0.10)
Devices that become hot to the touch use more energy than similar devices that don't	External cue	7 (91%)	6 (71%)	4 (100%)	3.8 (0.11)
Devices that need to be cooled while they are working use a lot of energy	Component	2 (100%)	0 (–)	1 (100%)	3.8 (0.11)
LED lights do not use a lot of energy	Component	4 (100%)	2 (100%)	1 (100%)	3.7 (0.20)
Heating or cooling something takes a lot of energy	Function	6 (71%)	6 (100%)	6 (75%)	3.6 (0.13)
Boiling water and turning it into steam requires a lot of energy	Function	5 (50%)	6 (56%)	3 (67%)	3.6 (0.15)
Appliances that move or heat water use a lot of energy	Function	7 (0%)	7 (64%)	3 (67%)	3.4 (0.16)
Devices with heating elements use a lot of energy	Component	5 (50%)	5 (86%)	7 (71%)	3.4 (0.20)
It takes less energy to heat something with microwaves than with heating elements	Component	5 (100%)	4 (100%)	3 (100%)	3.3 (0.25)
Thicker power cords are associated with more energy use	External cue	2 (33%)	1 (25%)	1 (100%)	3.2 (0.21)
Producing sound (music) does not require much energy	Function	1 (100%)	2 (100%)	1 (100%)	3.1 (0.24)
Devices that plug into a 240-volt outlet use more energy than devices that plug into a standard 120-volt outlet	External cue	6 (64%)	3 (75%)	4 (100%)	3.1 (0.27)
Devices with small or focused functions (for example, a desk lamp) need less energy than devices that are designed to perform large or broadcast functions (for example, an overhead lamp)	Function	9 (72%)	9 (76%)	4 (50%)	3.1 (0.21)
Devices that 'keep up the heat' or movement consume more energy					3.0 (0.22)
Devices that primarily heat or cool use more energy than devices with a primary function involving motion	Function	4 (0%)	3 (100%)	2 (25%)	3.0 (0.22)
A device that runs on its own circuit uses a lot of energy	Component	1 (100%)	0 (–)	0 (–)	2.9 (0.20)
Devices that have an initial heating up period consume more energy than devices that do not					2.8 (0.21)
Devices that either make lights dim/flicker or trip circuits when turned on use a lot of energy	External cue	4 (50%)	1 (0%)	1 (100%)	2.8 (0.26)
Devices that can run on batteries are low energy consumers	Component	2 (100%)	3 (100%)	0 (–)	2.8 (0.28)
Electronics that produce graphics (images) use more energy than other types of electronics	Function	4 (75%)	0 (–)	4 (100%)	2.8 (0.19)
The larger the plug a device has, the more energy it will use	External cue	1 (100%)	0 (–)	0 (–)	2.7 (0.24)
Heating takes more energy than cooling	Function	0 (–)	1 (100%)	0 (–)	2.6 (0.26)
Larger devices consume more energy					2.6 (0.16)
Performing a task quickly tends to take more energy than performing that same task more slowly	Function	5 (43%)	5 (67%)	3 (25%)	2.5 (0.26)
Quieter devices use less energy than ones that make noise (for example, a rattle or hum) when they are in operation	External cue	2 (100%)	1 (100%)	1 (0%)	2.4 (0.20)
Devices with a lot of components use more energy					2.4 (0.29)
Devices that charge other devices use more energy					2.1 (0.17)
Devices that have an energy label use more energy					2.1 (0.25)
Devices use less energy in the use phase compared to its use in a 'preparation phase'					2.1 (0.21)
Cooling takes more energy than heating	Function	0 (–)	1 (0%)	0 (–)	2.1 (0.21)
Devices that are related to each other (for example, DVD players and televisions) use similar amounts of energy					1.7 (0.24)

2.4. Survey 2: Assessing accuracy of heuristics

To evaluate the accuracy of the 24 heuristics that were extracted from the interviews as well as the heuristics we elicited from the literature, we went back to our 30 experts in February 2020 and asked them to assess each of the heuristics. (See Supplementary Methods 2.) In total, 16 experts responded to the request for further input (response rate = 53%). Using an online survey platform, we provided the experts with a set of 32 energy use heuristics: the 24 expert-derived heuristics and 8 heuristics extracted from a non-expert population [18] that did not overlap with the expert heuristics. These non-expert heuristics were included to assess how accurate experts find their own heuristics relative to those associated with novices, which are documented to already be in popular circulation [18]. The experts were asked to evaluate the general accuracy of these heuristics on a four-point scale (1 = "mostly inaccurate" to 4 = "highly accurate").

Note that both surveys are available in the Supplemental Text. 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.

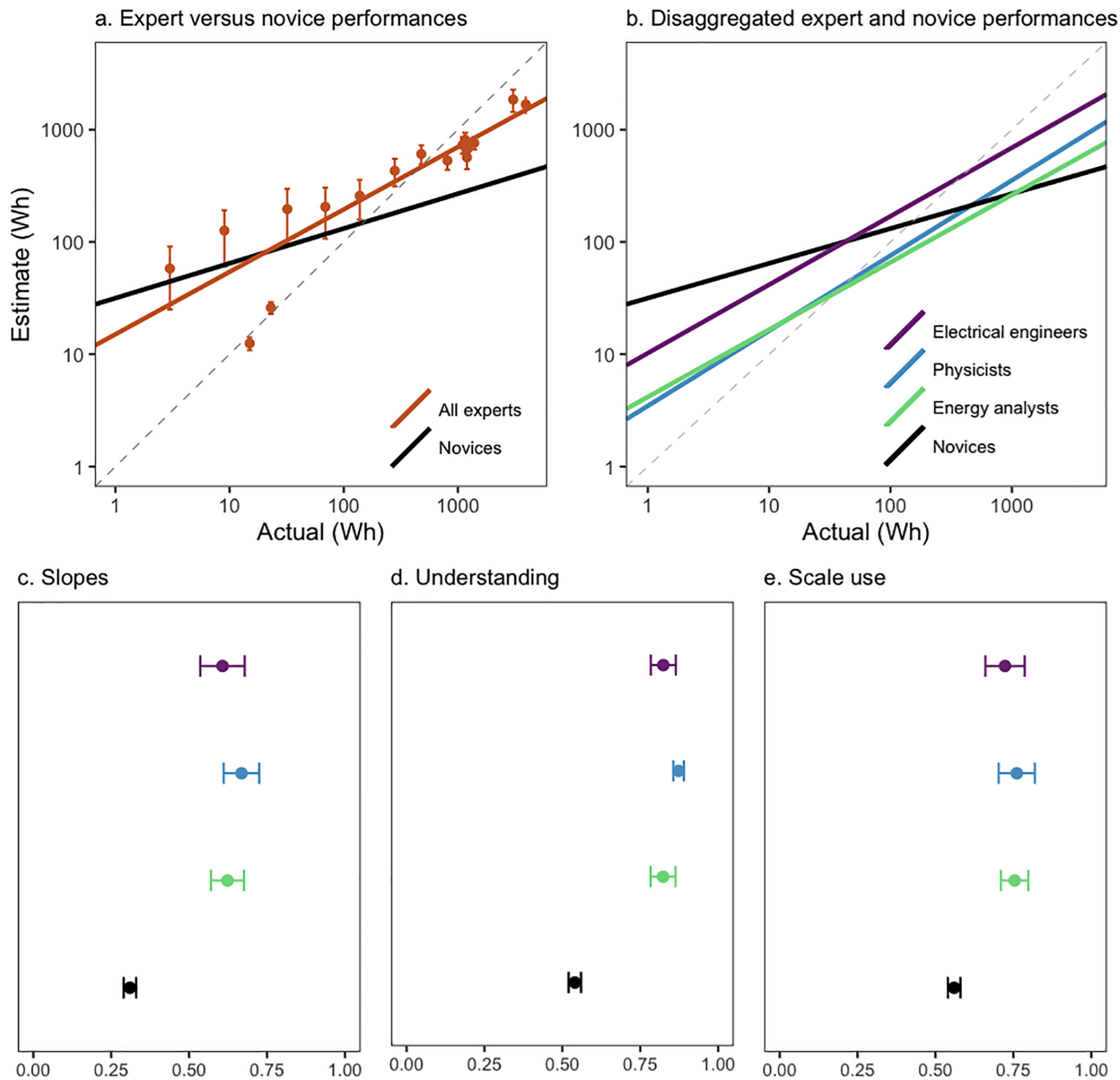

Fig. 1. Relationship between actual and estimated energy use. a. The estimated values for the 17 household devices, averaged across the 30 expert participants (orange dots), with the average expert slope line given in orange. The solid black line represents the average novice performance on the estimation task for the baseline control group in previous work [28]. The dashed line represents a slope of 1, a perfect relationship between estimated and actual energy use. b. The relationship between estimated and actual energy use for each of three expert groups: electrical engineers (purple), physicists (blue), and energy analysts (green). The novice reference value from the control group in previous work [28] is presented in black. c. Average estimate slopes for the three expert groups and the novice reference. d. Average understanding value (correlation between estimated and actual energy use) for the three expert groups and the novice reference. e. Average scale use value (ratio of standard deviation values for estimated and actual energy use) for the three expert groups and the novice reference. Points and error bars represent means ± standard error of the mean. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3. Results

3.1. Estimation task

Using an energy estimation task [6], we assessed performance by analyzing the relationship between the experts' estimated energy use values and the actual energy use of the corresponding devices. Experts were asked to estimate the units of energy used by each of 17 devices under the condition that these devices were in continuous use for one hour. We asked experts for "units of energy" (stating a 100-W light-bulb uses 100 units of energy in one hour) rather than wattages to match prior research and exercises with novices to allow for comparison. We measured each expert participant's overall energy estimation ability by calculating the slope of the best-fit line relating estimated and actual energy use on logarithmic scales.

The overall average estimation slope of our three expert categories are shown in Fig. 1a, as is the slope associated with the baseline novice group from previous work [28], while the mean slopes for the three expert groups are shown in Fig. 1b and 1c. In previous work [28], the mean estimation slope for unaided novices was 0.31 (SE 0.02). In comparison, the mean values of slopes for electrical engineers was 0.61 (SE 0.07), for physicists was 0.67 (SE 0.06), and for energy analysts was 0.62 (SE 0.05). There was no statistically significant difference in the mean slope values between the three expert groups ($F(2,27) = 0.26$, $p = 0.77$, $\eta^2 = 0.019$, $MSe = 0.037$). We note that each expert slope value is below 1, meaning that even the experts tend to overestimate the energy use of low-use devices and underestimate the energy use of high-use devices. That said, the expert slopes are far closer to 1 compared with novice slopes, and on average about twice the novice average slopes. The mean estimation slope for each expert group was significantly higher than the non-expert value (electrical engineers: $t(9) = 4.16$, $p < 0.01$, physicists: $t(9) = 6.20$, $p < 0.001$; energy analysts: $t(9) = 5.92$, $p < 0.001$).

The estimation slopes can be decomposed into two factors that comprise estimation accuracy: the correlation between a participant estimate and the true value, which measures *understanding* of the relative energy use of devices; and the ratio of standard deviations of the estimated and actual energy use values, which measures appropriate use of a *response scale* [28]. For both factors, values close to 1 indicate better performance. Through this decomposition, estimation slopes can be analyzed to better characterize in what ways experts outperformed novices in the estimation task.

Decomposition analysis indicates that experts in each group performed better on average than novices in terms of both underlying understanding of energy use and appropriate use of the response scale (Fig. 1d and 1e). Novice participants from previous work [28] averaged an understanding value of 0.54 (SE 0.02), a value substantially lower than the average for electrical engineers ($M = 0.82$, $SE = 0.04$), physicists ($M = 0.87$, $SE = 0.02$), and energy analysts ($M = 0.82$, $SE = 0.04$). Similarly, novice participants averaged a scale-use value of 0.56 (SE 0.02), a value that was exceeded by electrical engineers ($M = 0.72$, $SE = 0.06$), physicists ($M = 0.76$, SE 0.06), and energy analysts ($M = 0.75$, $SE = 0.04$). There are no significant differences in understanding ($F(2,27) = 0.70$, $p = 0.50$, $\eta^2 = 0.050$, $MSe = 0.012$) or scale-use ($F(2,27) = 0.12$, $p = 0.88$, $\eta^2 = 0.0090$, $MSe = 0.031$) values between the three expert groups.

Using a six-point scale (1 = not at all relevant and 6 = highly relevant), experts self-assessed the relevance of their expertise to the task of estimating the energy use of home appliances. On average, experts deemed their expertise relevant to estimating appliance energy use ($M = 4.6$, $SE = 0.26$). Self-perception of expertise relevance was a weak predictor of performance on the energy estimation task ($r = 0.24$, $p = 0.20$). The correlation between perceived relevance of expertise and understanding of device energy use was very low ($r = 0.08$, $p = 0.69$), while the correlation of perceived expertise and scale use was somewhat higher ($r = 0.29$, $p = 0.12$).

3.2. Choice task

We devised a set of nine choice tasks in which expert participants were asked to determine which of two or three common household devices or activities used the least amount of energy when used for the same amount of time. Each choice task exercise had a designated correct answer, which was the device in the set that had the lowest average rated energy use. For example, window air conditioner (~1157 W) was the correct choice in the set containing it and an electric oven (~3050 W). Across the nine choice task exercises, participants selected the correct choice 5.6 times on average, with individual scores ranging from 2 to 9 (perfect score). On average, electrical engineers answered 5.0 ($SE = 0.49$) choice task questions correctly, physicists scored 5.7 ($SE = 0.56$) correct answers, and energy analysts scored 6.0 ($SE = 0.30$) correct answers. There was no statistically significant difference in choice task performance between the three expert groups ($F(2,27) = 1.22$, $p = 0.31$, $\eta^2 = 0.083$, $MSe = 2.15$). Similar to the estimation task, the correlation between perceived relevance of expertise and performance on the choice task was weak ($r = 0.10$, $p = 0.59$).

3.3. Relationship between choice and estimation tasks

To assess the connection between the choice task score (9 items, 1 for correct and 0 for wrong, $M = 5.6$, $SE\ 0.27$) and estimation task slope ($M = 0.63$, $SE\ 0.03$), we calculated the correlation between the number of correct answers given on the choice task and the slopes of the estimation task. Across all 30 experts, the correlation between choice task score and estimation slope was quite low ($r = 0.06$, $p = 0.73$). There was some variation of this correlation between expert groups, as the correlation for electrical engineers was negative ($r = -0.18$, $p = 0.62$) while the correlations for physicists ($r = 0.17$, $p = 0.60$) and energy analysts ($r = 0.31$, $p = 0.39$) were positive. The negligible overall correlation between choice task score and estimation slope is consistent with prior research done that showed that the correlation between the choice task (20 items, $M = 12.1$, SE 0.12) and estimation slope (control condition $M = 0.31$, SE 0.01) was also weak and positive ($r = 0.20$, $p < 0.001$) in the control condition [28]. Note that the choice task items were different in the previous study, which does not allow for perfect comparison with the data presented here.

3.4. Expert heuristics

To capture expert heuristics, we analyzed the transcripts derived from the expert interviews using the protocol analysis method to extract a list of 24 heuristics employed by experts during the choice task (see heuristics listed in Table 1).

The set of heuristics can be divided into three general types based on how they relate to thinking about a device's energy use. The most common heuristics type relates to function – the tasks that the device is designed to perform. Eleven of the 24 heuristics belonged to the *function* type. Examples of specific device functions highlighted by experts include heating and cooling, producing sound, and moving water. Typically, when commenting on functions, experts expressed a general rule about the absolute or relative energy cost of a function, as in, "appliances that move or heat water use a lot of energy" or "producing sound does not require much energy."

The second most common heuristic type focused on the energy use by specific *components* or systems associated with devices. Seven of the heuristics were of this type. Most of the rules of this type assessed what could be inferred about the energy use of a device based on the presence or absence of specific components within the device, as in, "devices that can run on [small] batteries are low energy consumers." One rule, however, related to the household circuit on which a device is powered ("A device that runs on its own circuit uses a lot of energy"), which can be thought of as an external "component" rather than an internal one.

The final six heuristics made reference to *observable cues* that indicate higher levels of energy use. These are cues that do not rely on understanding the function of a device or on knowing its components, but rather require making observations about the physical presence or ambient effects of the device (e.g., its size or whether it gets hot to the touch when running). The heuristics of this type link the cues to judgments about energy use, as in, "the larger the plug a device has, the more energy it will use."

In the 290 instances of heuristic use documented across the 30 expert interviews, a majority (54%) of the heuristics used were *function*-based heuristics. *Components* (24%) and *external cues* (22%) heuristics were both used less frequently on average than *function* heuristics. There were some differences between the expert groups in terms of what kinds of heuristics were used. Relative to other groups, electrical engineers more frequently used external cues (29% of all heuristic use versus 17% for physicists and 16% for energy analysts). Physicists were more likely to reference the function of devices (62% versus 50% for electrical engineers and 51% for energy analysts), while energy analysts were more likely to employ a heuristic based on the components of the devices in the choice task (33% versus 20% for electrical engineers and 22% for physicists). The total number of instances of heuristic use by electrical engineers (119) and physicists (102) was higher than that of energy analysts (69).

Success with the choice task required selecting the lowest energy-using device in a set of two or three devices or activities. Many experts approached this task by eliminating options they viewed as clearly using more energy than at least one of the other devices. For example, many experts noted that an electric space heater (~1290 W) would use more energy than an electric blanket (~197 W) and so were able to quickly dismiss the space heater without needing to attend to it closely. (In the words of one physicist, "So, I'm going to say the blanket's less than the space heater just because you're trying to heat up less. Space heater is trying to heat up the whole room; the blanket, it's local heat.")

To assess the quality of the 24 expert heuristics, we counted the number of choice task responses where the heuristic was used to reach the correct answer and divided this sum by the total number of instances when the heuristic was used (see the third column in Table 1). The resulting conditional probability – the frequency of arriving at the correct answer if the heuristic was used – provides a simple measure of heuristic usefulness, with higher values suggesting that a given heuristic was useful in reaching a correct judgment in the choice task. The heuristics were associated with varying levels of success in choosing the correct choice task response. Associated success rates ranged from 0% (when used, a correct answer was never given, e.g., "cooling takes more energy than heating") to 100% (when used, a correct answer was always given, e.g., "devices that need to be cooled while they are working use a lot of energy"), with a median success rate of 71%. Only four heuristics had a success rate less than chance on a two-item choice task (i.e., was<50%).

Analyzing how accurate experts are on the choice task is not a conclusive measure of heuristic quality. Often, multiple heuristics were used to generate a single choice task response and thus we cannot directly attribute success or failure in the choice task to a single heuristic in these cases. The assessment metric does not tell us about the accuracy of heuristics *in isolation*, a metric that required the second round of data collection described below.

3.5. Follow-up survey

We asked the same expert participants to evaluate the general accuracy of the 24 heuristics that emerged from the interviews. We also included eight (of the 24) novice-derived heuristics identified by other researchers [18] for evaluation, which were selected so as not to overlap with the expert heuristics (see Supplementary Table 2 for the entire list of the novice heuristics). Table 1 (Column 4) provides the complete set of average expert evaluations of the 32 heuristics. Averaging across the 16 experts who responded to this second survey, 21 of the expert heuristics were deemed to be at least somewhat accurate (i.e., they scored above the neutral mark of 2.5), while 3 heuristics had an average score on the "inaccurate" end of the scale. In contrast, the majority of novice-derived heuristics that we used (5 out of 8) were deemed by our panel of experts to be somewhat inaccurate (i.e., their average score was below 2.5). Overall, the accuracy evaluation scores for expert heuristics were significantly higher than those of the novice heuristics ($M = 3.1$ versus $M = 2.4$, $t(30) = 4.32$, $p < 0.001$).

4. Discussion

On average, expert-level electrical engineers, physicists, and energy analysts all outperformed the novice baseline on an energy estimation task. In comparing these performances, we find an affirmative answer to our first research question: experts in energy-related fields do have more accurate estimates of home energy use than novices. (Notably, and consistent with the Dunning-Kruger effect [34], we also find that our expert sample tended to undervalue the relevance of their expertise to the estimation task, as evidenced by the modest correlation between performance and self-rated expertise.) Improving novice understanding of energy use, and thereby potentially improving the uptake of impactful conservation and efficiency measures, might in part be achieved by documenting the heuristics by which experts outperform novices.

Addressing our second research question, we identify 24 unique expert heuristics used to make judgments about energy use by household devices. We find that heuristics related to device function were most prominent in terms of both the number of separate heuristics and the frequency of heuristic use. This prominence may suggest that sorting devices into functional categories (e.g., devices that heat or cool and devices that create motion) is a key technique used by experts for discriminating between tiers of energy use. Relatedly, temperature change emerged as a dominant theme, with nine heuristics across the three heuristic types addressing heating and cooling in one form or another. Indeed, five of the seven most accurate heuristics (as judged by expert participants) relate to heat. Altogether, the responses of our experts suggest that making distinctions between devices that heat or cool and those that do not is paramount. Creating motion (as with a treadmill) and interaction with water (as with a washing machine or water heater) were two other frequently employed discriminant categories.

Concerning our third research question, we find that, with minor exceptions, the expert heuristics were judged to be more accurate than a comparison set of cultural heuristics used by novices [18]. Accordingly, supplementing or replacing novice heuristics with expert heuristics may be an effective way of improving public judgment and decision making concerning home energy use. Past research has demonstrated that an expert heuristic can be used to improve energy-related estimations [28], where introducing a single expert heuristic – "large appliances that primarily heat or cool use a lot more energy than people think" – improved novice performance on both understanding and scale use in the energy estimation task.

It is important to note that 13 of the novice heuristics noted in previous work [18] were similar in content to 6 of the expert heuristics identified here, including highly accurate heuristics relating to heating. While this overlap in content suggests that novices may already use some of the same heuristics as experts, part of what distinguishes novices and experts is the judicious use of heuristics, that is, knowing when and how to apply or not apply them. Further, the poor accuracy of novice-exclusive heuristics confirms past research suggesting that novices often attend to low-relevance energy-use cues [15–17], which may compete with more accurate and useful heuristics for salience.

The pool of experts who participated in this research belonged to three different groups, and this breadth of expertise diversified the data we collected (consistent with past calls for diversity in eliciting expert judgments [35]). We anticipated that different expert groups would bring different vantage points to the issue of home energy use and we observe modest differences in how experts approached the tasks of judging home energy use. For example, energy analysts tended to use heuristics less than electrical engineers or physicists. Further, each group, relative to the others, tended to favor a particular type of heuristic (i.e., electrical engineers used *observable cues* more often, physicists used *function* heuristics more often, and energy analysts used *component* heuristics more often). Despite these differences, each group outperformed the previously established novice baseline and there was no significant difference between the three expert groups in the performance on either the estimation task or the choice task.

Given that part of expertise is knowing how to separate relevant and irrelevant information, the spontaneously generated heuristics may be considered an indicator of what information our experts deemed most important in judging energy use. Though the experts came from diverse backgrounds, there was a general convergence across experts in terms of the heuristics that were used. Accordingly, our diverse sample of experts involved in this study provides a form of corroboration that the list of heuristics contains the critical ideas needed to better assess device energy use.

The energy estimation task was successful in differentiating between experts and novices (as shown in Fig. 1). That said, expert performance on the estimation task was only weakly correlated with the other measure of judgment aptitude, the choice task. This weak correlation, while puzzling, suggests that the two tasks may require different judgment skills or may have been approached in different ways. We hypothesize that assessing devices simultaneously during the choice task and in much more real-world settings of energy use may have created noise in the task leading to lower accuracy. The estimation task required experts to judge one device at a time without comparing one device to another – this required thinking of energy use in terms of ratio values, explicitly deciding for example whether an oven uses two or three times more energy than a window air conditioner. In contrast, the choice task called on experts to think ordinally (i.e., ordering as first, second, etc.) about the energy used by devices, choosing the lowest energy user without necessary regard for the magnitude of difference between items in the choice set (e.g., a window air conditioner uses some amount less energy than an oven). Future research can be designed to more fully investigate why there is such a low correlation between the estimation and choice tasks, while keeping in mind that these two measures are distinct in terms of what judgment processes they may prompt.

This research was conducted as part of a larger effort to improve public understanding of energy use, to aid the uptake of effective efficiency and conservation measures at the household level. Previous research has measured energy-use perception accuracy by the general public [6] and documented the heuristic processes and cues that energy novices use to make judgments [15,17,18]. A central contribution of our work to this body of literature is the systematic documentation of expert energy heuristics. Assuming expert performance on judgment tasks represents a realistically achievable upper bound for novice performance, this research indicates the degree to which novice performance could be improved. Further, by cataloging a set of expert energy heuristics, our work establishes a set of rules and principles that, when transferred to novices, may serve to increase the accuracy of energy understanding and possibly choices.

Further research is required to understand the capacity of the 24 expert heuristics to improve novice energy judgments and real-world decisions. Such research would first need to determine whether these expert heuristics are truly helpful decision aids, then to assess the combination(s) of heuristics that are most effective in improving judgment. We also need to assess whether these heuristics help with real-world decision making, as decision aids have done in the domains of healthcare [36,37], investing [38], and marketing [39]. While in theory access to more high-quality heuristics could lead to greater improvements in performance than access to fewer high-quality heuristics, in practice performance improvement may plateau at a relatively small number of heuristics because a larger set of heuristics may become too difficult to remember or apply appropriately [40–42]. Further, the heuristics collected in this study vary in terms of accuracy (as assessed by experts), breadth (i.e., some can be applied to a wide range of devices while others are device-specific), and type (i.e., function, components, and observable cues). Future studies can examine the “ecology” of heuristics, testing what number and types of heuristics are associated with the greatest improvements in energy judgment aptitude. If the collected expert heuristics can improve energy-related decision making, they may be a useful new component for education programs designed to foster reduced energy use [8,18].

There are many limitations to our work. First, our sample of experts was convenience based, and should not be seen as representative of the three expert groups, which would be challenging to come by. Second, our sample of examples was heavily skewed towards males, with only one expert out of ten in each group identifying as female. While we have no reason to believe our results would have been substantially different, we nonetheless believe the study would have been improved by greater gender parity in our sample. Third, the population of experts targeted in this research was skewed towards those with advanced academic credentials; additional insights might have come from including those with different markers of expertise, including electricians and technology hobbyists. Fourth, the choice task from which the list of heuristics was extracted focused on energy use by household devices and was not designed to capture other heuristics relating to general energy-use behaviors, such as where to live or what kind of transportation to use which are important domains for reducing energy use. Fifth, while we coded specific answers in the choice task as being “correct,” several of the devices used for the choice task are associated with a range of wattages. (For example, models of microwaves can range between 700 W and 1400 W.) Accordingly, the assignment of one device as being “correct” is contingent on assumptions about what comprehends the prototypical or mean version of the device (see Supplementary Methods 1 for actual energy use values).

Author contributions

J.K. and S.Z.A designed the research, J.K. collected the data, J.K. and S.Z.A. analyzed the data, J.K. and S.Z.A. wrote the paper.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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