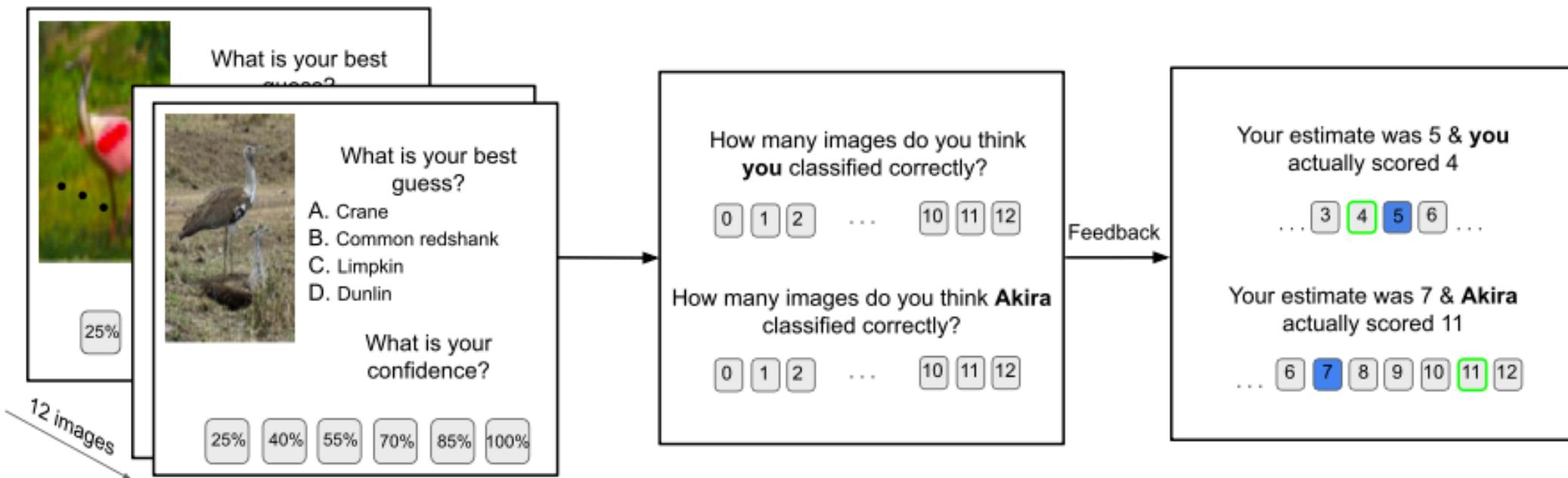


Figure 3

Illustration of the Empirical Paradigm for Self- and Other-Assessment



Note. Participants go through a series of classification problem sets requiring participants to discriminate between different types of animals in a four-alternative forced-choice task. After classifying 12 images that constitute a problem set, participants proceed to the assessment phase, where they estimate the number of items they and another person answered correctly. The assessment phase is followed by feedback (if provided) on the actual number of items answered correctly. Numbers in blue and green show estimates and true scores, respectively. The scores of the other (target) person are based on selected participants who previously went through the experiment. A number of different names, including Akira, are used to reference the other person. See the online article for the color version of this figure.

Figure 1: 1743736588664

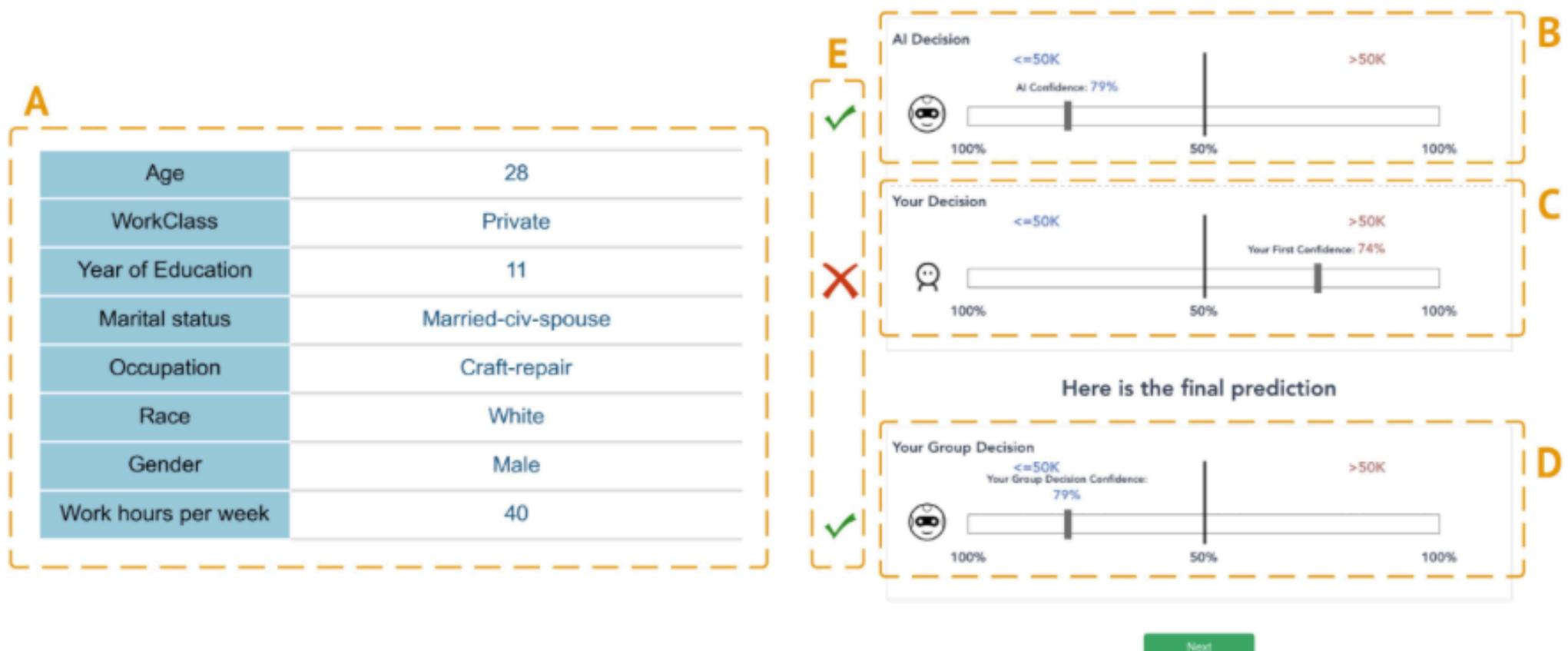


Figure 3: Interface of the income prediction task (an example on a task instance from stage 2 and under the paradigm where AI acts as a peer collaborator). A: The profile table of the income prediction task including 8 attributes. B: AI prediction and confidence level about the task. They are only presented in stage 2, after users report its prediction and self-confidence at first. C: Users' prediction and self-confidence level about the task. At the beginning of each task from each stage, users need to report and submit their decision and self-confidence here at first. D: The final decision and confidence about it, only applying to stage 2. For the paradigm where AI acts as an advisor, users need to make the final decision here. For the other two paradigms, the system would make the final decision according to the rules and present the result here. E: Real-time correctness feedback for users' decision (stage 1, 2 and 3), AI's decision (stage 2), and the joint final decision (stage 2): under conditions with real-time feedback, it would be displayed after users submit their own decisions in stages 1 and 3, and after the final decision is made in stage 2.

Figure 2: 1743736644799

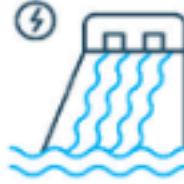
A B S T R A C T

How actors perceive the transition pathways towards sustainable energy production and use will likely influence their support in their everyday behaviour and political engagement towards the energy transition. Mapping actors' mental models of the drivers of the energy transition can provide key insights into such perceptions. The present study is the first to systematically map mental models of the drivers of the energy transition, compare mental models between actor groups, and explain differences in mental models with political orientation and worry about climate change. We mapped mental models about the energy transition among a sample of experts ($N = 25$), and representative samples of Dutch ($N = 299$) and Norwegian ($N = 313$) citizens. Participants visualised their perceptions of the causal relations of different energy transition pathways by drawing a diagram using a standardised tool to map mental models (M-Tool). The results demonstrate (1) a key focus in the mental models on renewable energy generation such as solar panels, wind farms, and hydropower, (2) that expert mental models are more focused on policy pathways compared to citizen mental models, (3) that mental models of actors leaning towards the political right focus less on individual behaviour than left-leaning actors, and (4) that climate change worry results in more focus on individual behaviour and policy pathways in the mental models. Policymakers could use these insights to engage citizens with the energy transition, for example, by tailoring their messages to the mental models of the target group.

Figure 3: 1743736704947

Table 2

Energy transition pathway concepts available to participants in the mental model task with their definitions and icons.

Icon	Concept	Definition
	Science	The pursuit and application of knowledge and understanding of the natural and social world following a systematic methodology based on evidence.
	Hydropower	A renewable energy source where waterfalls or streams are used to produce electricity.
	Wind farms	An area of land with a group of energy-producing windmills or wind turbines.
	Nuclear power	The use of nuclear reactions to generate energy that boils water for a steam engine to make electricity.
	Energy saving	The effort made to reduce energy consumption.
	Climate compensation	Investments in climate measures that compensate for the emissions from activities.
	Public transportation	A system of vehicles such as buses and trains that operate at regular times on fixed routes, available to members of the public.
	Environmental education	A process (at school or work) that allows individuals to explore environmental issues and take action to improve the environment.
	Energy efficient houses	An energy-efficient home is designed to reduce energy use.
	Subsidies	A sum of money granted by the government to keep the price of a commodity or service low.
	Solar panels	A panel designed to absorb sunrays as a source of energy for generating electricity or heating.
	Energy efficient home appliances	An electrical device in your home that uses relatively little energy to provide the power it needs for a task.
	Electric cars	A car that is powered by electricity from a battery that requires recharging.
	Regulations	Rules or directives made and maintained by a legislative authority.
	Carbon capture and storage	The process of capturing and storing carbon dioxide (CO ₂) to prevent its release into the atmosphere.

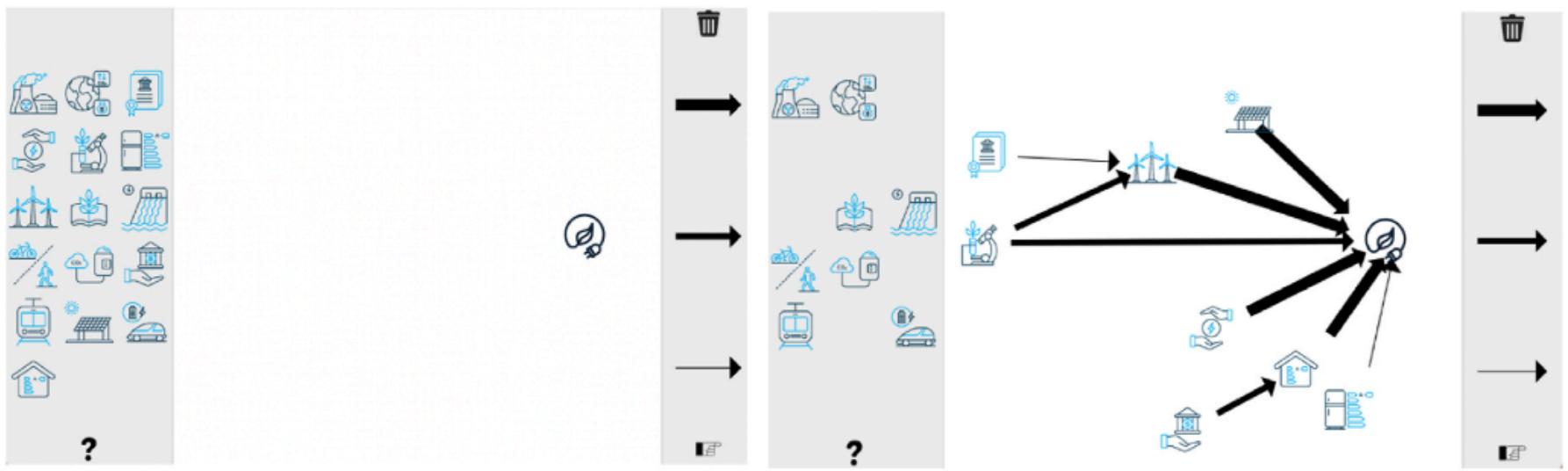


Fig. 1. Mental model mapping screen in M-Tool (left panel) and example of a mapped mental model (right panel). The fixed set of energy transition concepts is on the left panel, the weighted arrows are in the right panel, and the mapping canvas is in the middle, with the target variable of the energy transition on the right.

Figure 5: 1743736761405

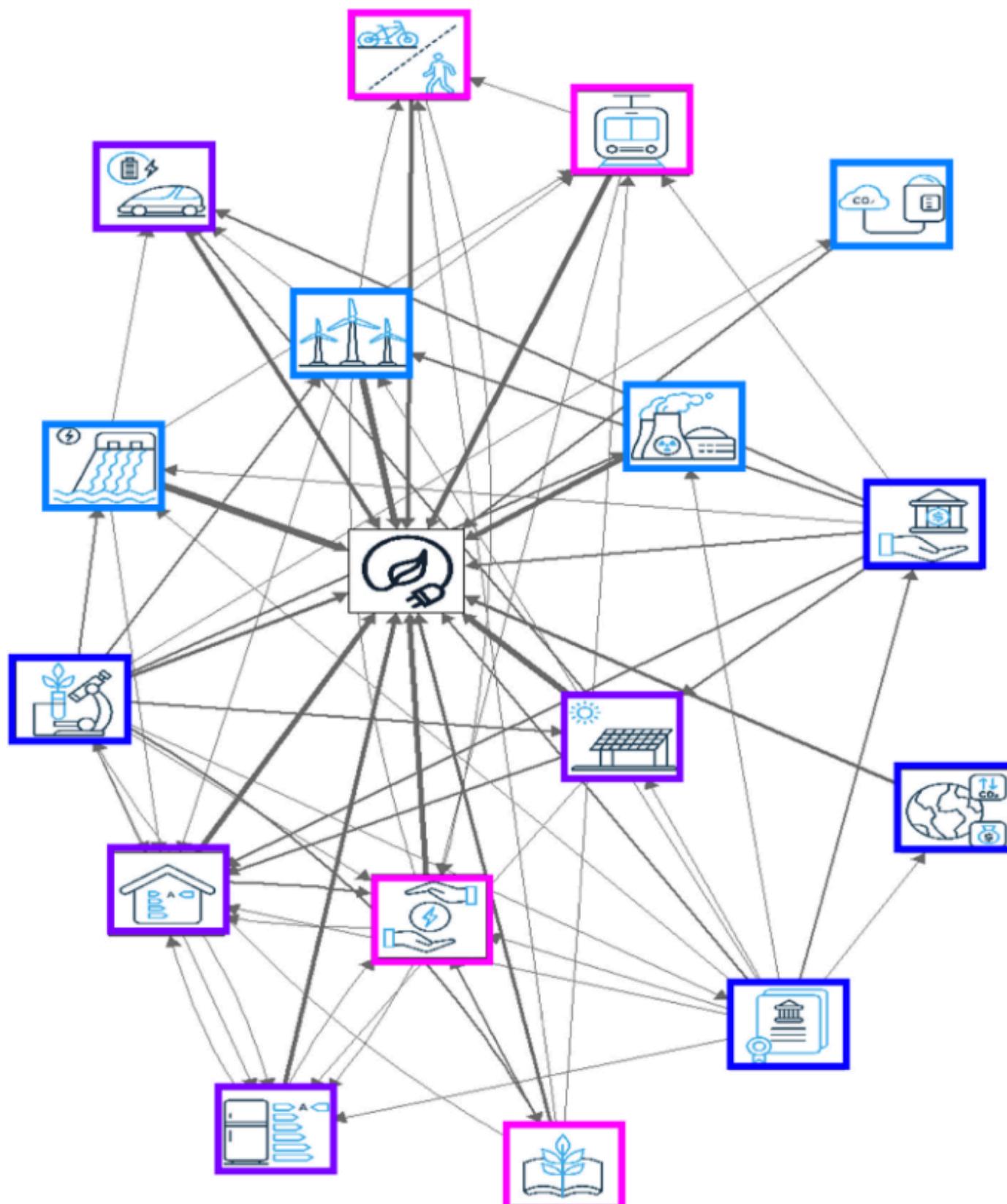


Fig. 2. Aggregate mental model of all samples. Arrow width indicates the sum of the weights of the connections of the individual mental models (thicker arrows indicate stronger connections). Note: Only connections with an above average aggregated weight are displayed. Border colours indicate concept clusters (pink = Individual behaviour, dark blue = Policy, purple = technology - consumer adoption, light blue = technology – government adoption). Note: The icons presented to participants did not have coloured borders.

How confident are you that the model you drew is a good representation of the most important aspects of the energy transition?

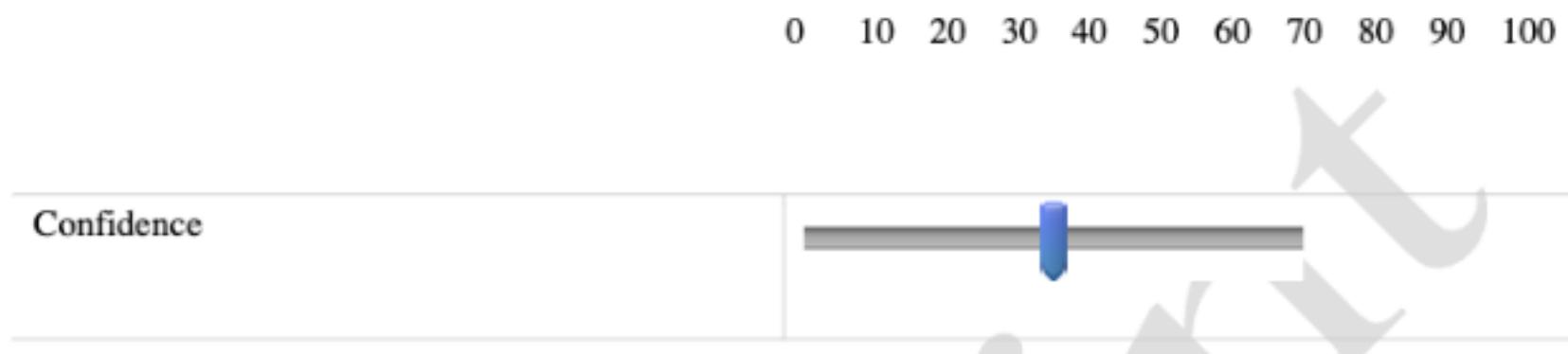
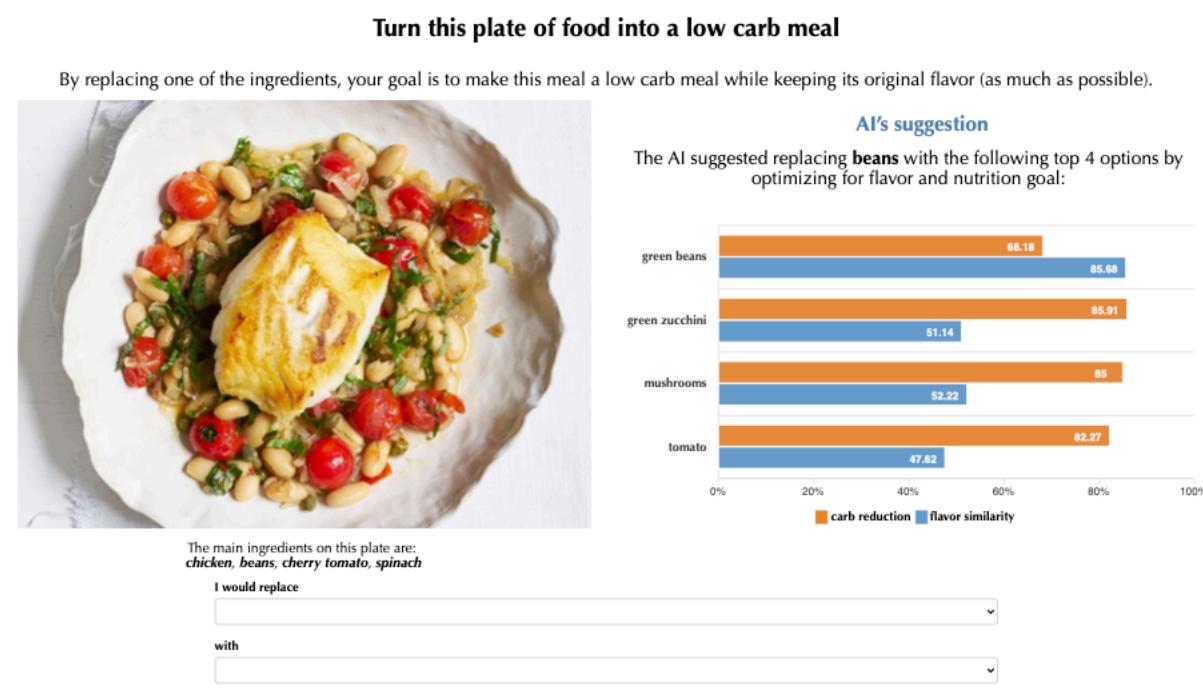


Figure 7: 1743736858915

Buçinca, Z., Malaya, M. B., & Gajos, K. Z. (2021). To Trust or to Think: Cognitive Forcing Functions Can Reduce Overreliance on AI in AI-assisted Decision-making. Proceedings of the ACM on Human-Computer Interaction, 5(CSCW1), 1–21. <https://doi.org/10.1145/3449287>



(a) explanation (SXAI)



Figure 8: 1743736878632

AI-assisted decision-making or for which we found to have appropriate analogs in the AI-assisted decision-making domain:

- *Asking the person to make a decision before seeing the AI's recommendation.* Prior studies in human-AI decision-making have shown the anchoring bias that occurs by presenting people with AI's recommendation before allowing them to make a decision first [26]. People made better decision when they saw the AI's recommendation after making an unassisted decision.
- *Slowing down the process.* As shown by other HCI researchers, simply delaying the presentation of AI recommendation can improve outcomes [50].
- *Letting the person choose whether and when to see the AI recommendation.* There is evidence that showing unsolicited advice that contradicts a person's initial idea may trigger reactance (resistance to the advice) [21]. To prevent this, one could only show AI recommendations when a person requests it.

A growing number of studies demonstrate, however, that people prefer simpler constructs, even though they learn more and perform better with more complex ones. Visualization literature reveals that visual difficulties, while not necessarily preferred, improve participants' comprehension and recall of the displayed content [29]. Recent education research also indicates that students preferred and thought they learned more with easier, passive instructions than with more cognitively demanding, active instruction. But when evaluated objectively, their actual learning and performance was better with the more cognitively demanding, active instruction [18]. Therefore, while cognitive forcing functions may enhance user performance, there likely exists a tension with user preference of the system.

3 EXPERIMENT

We conducted an experiment with 3 different cognitive forcing interventions, two simple explainable AI conditions, and a no-AI baseline, to examine whether cognitive forcing functions are successful in reducing human overreliance on the AI when working on a decision-making task. Specifically, we hypothesized that:

H1a: Compared to simple explainable AI approaches, cognitive forcing functions will improve the performance of human+AI teams in situations where the AI's top prediction is incorrect.

And, consequently:

H1b: Compared to simple explainable AI approaches, cognitive forcing functions will improve the performance of human+AI teams.

However, because cognitive forcing functions cause people to exert extra cognitive effort, we expected that there would be a trade-off between the acceptability of the design of the human+AI collaboration interface and its effectiveness in reducing the overreliance: people would over-rely less on the AI when they were forced to think harder, but they would prefer such interfaces less than those that require less thinking. Thus, we hypothesized that:

H2: There will be a negative correlation between the self-reported acceptability of the interface and the performance of human+AI teams in situations where the AI's prediction is incorrect.

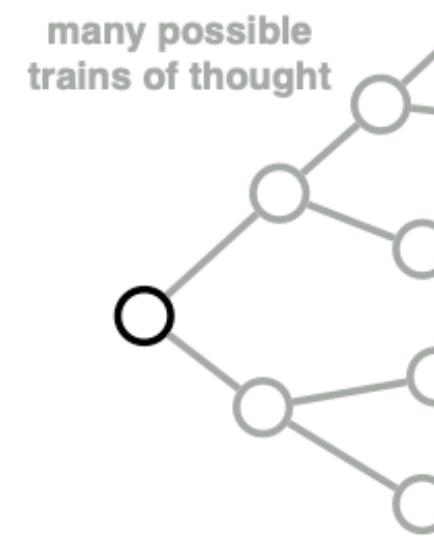
3.1 Task description

Accessing experts such as judges, or clinicians for experiments is notoriously challenging and costly. We, therefore, designed the task around nutrition as an approachable domain for laypeople.

Figure 9: 1743736893611

Figure 11

Experiment 3: Formalizing in



Note. When all information is equally available. Highlighting some information away from others. This in turn m

Figure 12

Experiment 3: Example inform

Clicks to reveal box	Prize
1	A: 20 p
2	B: 9 p
3	C: 1 p

Note. All click costs were initially equal. At the start of each trial, the agent chose a point. On control trials, a highlight

Optimal nudging for cognitively bounded agents: A framework for modeling, predicting, and controlling the effects of choice architectures

Figure 14

Experiment 4: Problem construction procedure

1.) Generate payoff matrix and set all but three random costs to two points

Basket 1	Basket 2	Basket 3	Basket 4	Basket 5	Basket 1	Basket 2	Basket 3	Basket 4	Basket 5
4	5	3	7	2			3		
7	3	7	6	7					7
6	7	4	5	6					
7	7	5	3	6					
5	3	3	6	7					7



2). Generate optimal, extreme, and random modifications

Optimal modifications

Basket 1	Basket 2	Basket 3	Basket 4	Basket 5
		3		2
				7
6				
7				
				7

Extreme modifications

Basket 1	Basket 2	Basket 3	Basket 4	Basket 5
		3		2
				7
		7		
				7
				7

Random modifications

Basket 1	Basket 2	Basket 3	Basket 4	Basket 5
		3		
				7
7	7			
			6	7



3). On each trial, select modification type and sample feature weights

Prizes	Basket 1	Basket 2	Basket 3	Basket 4	Basket 5
A: 8 points			3		2
B: 1 point					7
C: 11 points	6				
D: 5 points	7				
E: 5 points					7

Note. The weights were not known when constructing the nudges.

Figure 4*Experimental interface for Mouselab*

Prizes	Basket 1	Basket 2	Basket 3	Basket 4	Basket 5
A: 3 points	2		3	4	
B: 2 points	7				7
C: 2 points	7	4		2	
D: 21 points	7		8	6	
E: 2 points	9				6

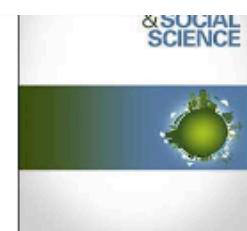
Total click cost: 10 points

You won 2 A prizes, 7 B prizes, 7 C prizes, 7 D prizes, and 9 E prizes, totaling 199 points.

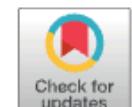
Total earnings (prize values minus click cost): \$0.063.

Note. On this problem, participants chose between five baskets, represented by the table columns. Each basket has five different prize types, with the value of each of these prizes given in the leftmost column. To reveal prize counts, participants could click on the corresponding red box once, with each click costing one point. At any point, participants could stop choosing and select a basket (e.g., basket 1 in this example). The participant then earned a bonus determined by the total value of the prizes in the selected basket minus the cost spent revealing boxes (30 points are worth one cent).

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

**Energy Research & Social Science**journal homepage: www.elsevier.com/locate/erss

Original research article

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

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

*Human-Technology Interaction Group, Eindhoven University of Technology, PO 513, 5600MB Eindhoven, the Netherlands***ARTICLE INFO****ABSTRACT**

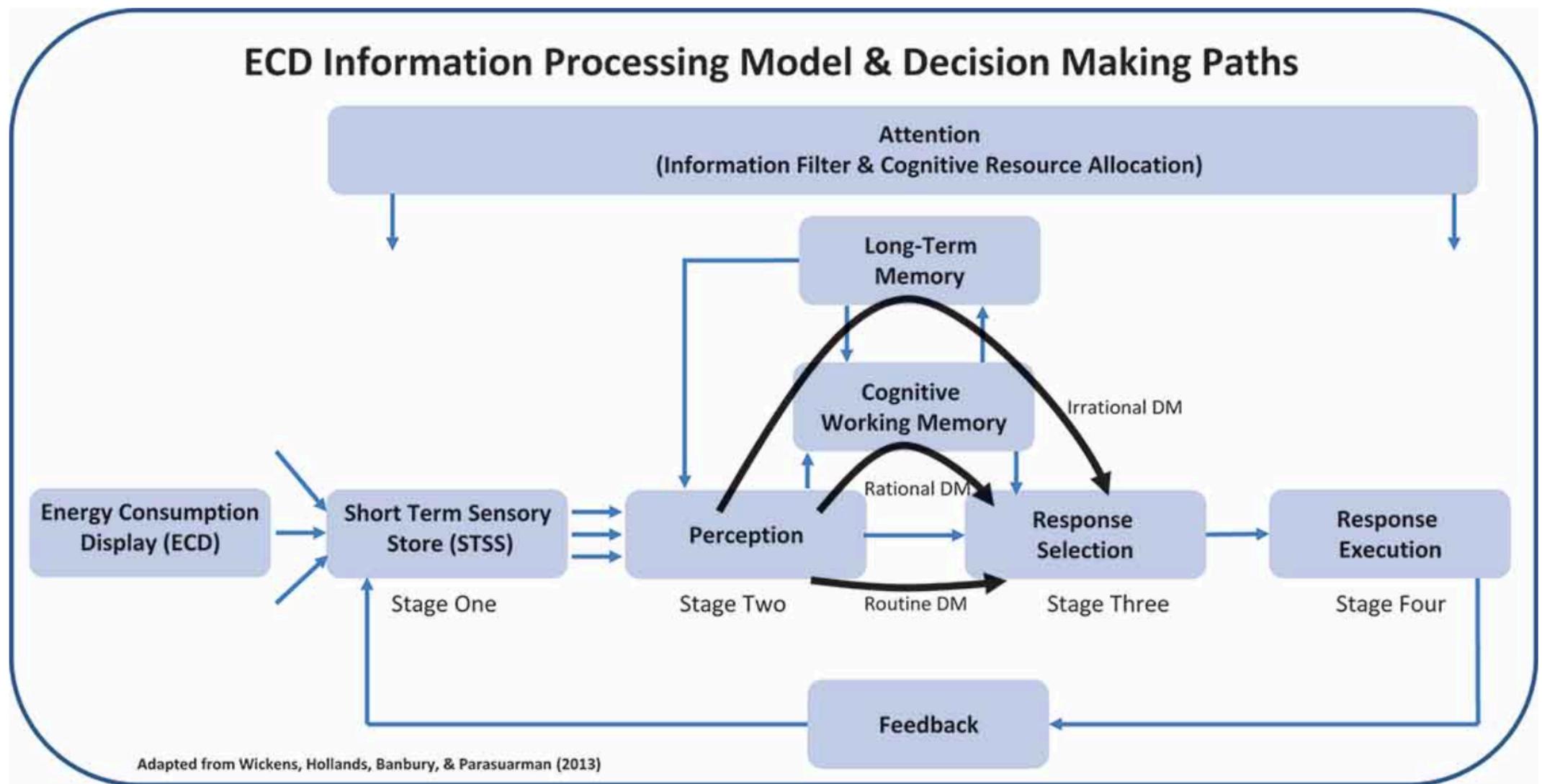
Keywords:
Conservation advice
Energy efficiency
Rasch model
Recommender systems

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

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

Figure 10: 1743737067293

Fig 2. ECD information processing model and decision-making paths.²²



[Display full size](#)

Within the cognitive memory functions, two forms of memory are distinguished, working memory and long-term memory,²² as shown in Figure 2. Working memory contains information under current consideration, from our senses and cognitive analysis capabilities. It is here that demographic factors, market segmentation, and other real-time information is incorporated in the decision making process. The working memory's key constraint is its limited capacity only to hold a few items at a time under consideration. Bettman et al.²⁴ identify the number of items to be held in the working memory to be seven items plus or minus two. This limitation drives two important consequences. First, people do not transform the information, but rather process it in the form presented as seen on displays. The non-transformation of the information explains why the same information presented in different formats can have different impacts on an individual's decision—known as the concreteness principle.²⁴ The second factor of the working memory limitation to seven items is that people employ heuristics to process information. Heuristics are

Figure 11: 1743737086145

Examining community-level approaches to enhance household electricity savings

Devon Wemyss  · Roberta Castri ·
Francesca Cellina · Vanessa De Luca ·
Evelyn Lobsiger-Kägi · Vicente Carabias

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Abstract To test the effectiveness of a community-level approach compared to a traditional collaborative approach on engaging people to change their household electricity-use habits, a mobile application, called Social Power, is developed to provide meter feedback in two gamified environments. The project aims at stimulating social engagement and promoting behavioral change to save electricity at the household level by forming teams of neighborhoods from four Swiss cities. The household participants are assigned to one of two teams: either a collaborative team where citizens in the same city try to reach a fixed electricity savings target collectively or a competitive team which tries to save the most electricity in comparison to another city. The collaborative and competitive gamified structures are run in parallel as a 3-month experiment (February to May 2016) involving 100 households.

household electricity-saving behavior. Energy Efficiency, 11(8), 2057–2075. <https://doi.org/10.1007/s12053-018-9691-z>

Individual feedback

The Social Power app displays the participant's progress in earning points, as well as the individual electricity use in the energy diary (Fig. 3b), which shows the hourly

alone tends to be ignored after a time when one's own electricity use patterns are known (Hargreaves et al. 2013), the disruption in one's awareness of own habits can be used as an opportunity to embed new habits before the novelty is lost (Verplanken et al. 2008).

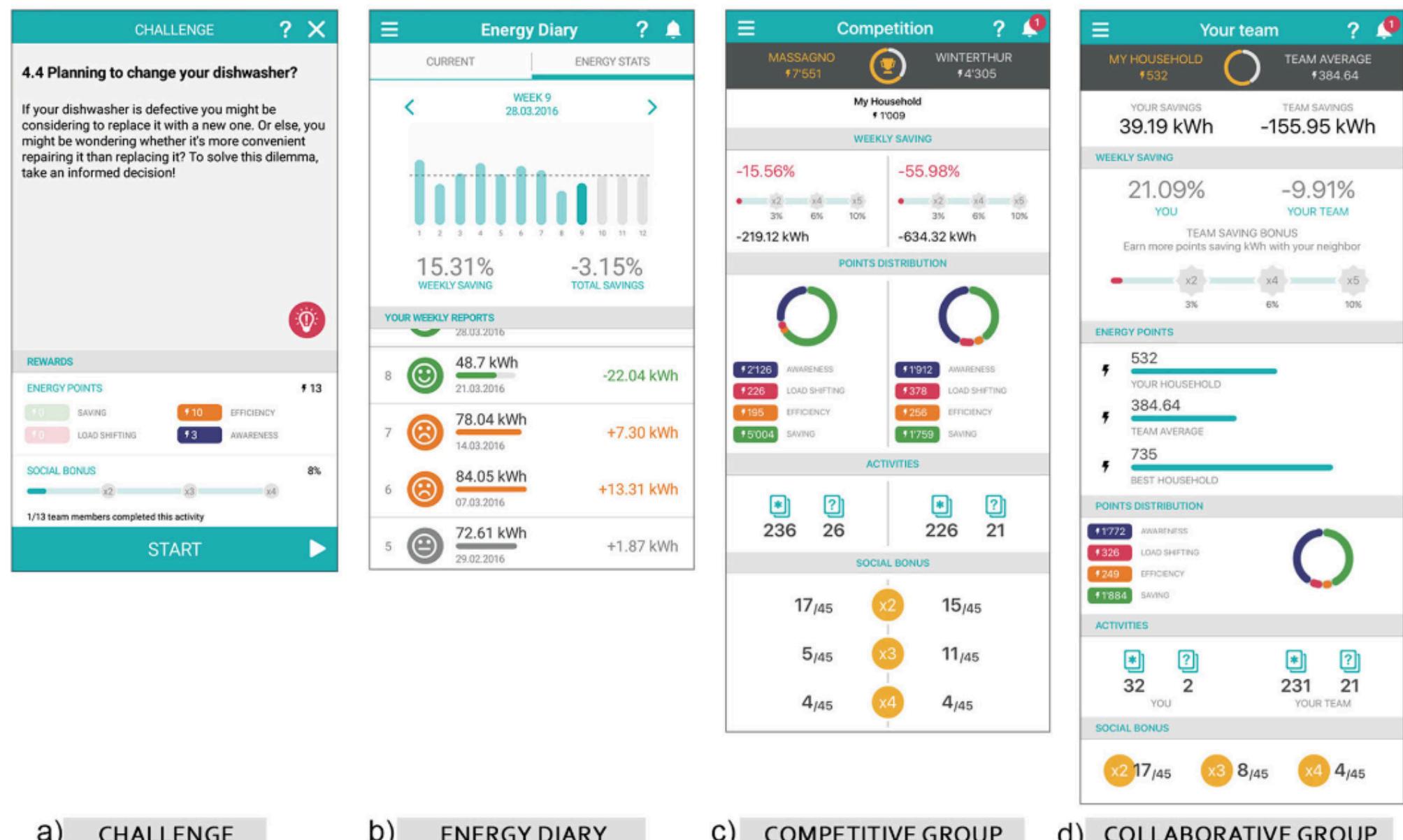


Fig. 3 Screenshots of the Social Power app. **a** First step of an activity. **b** Energy Diary with weekly consumption reports. **c** Competition feedback. **d** Collaboration feedback

Figure 12: 1743737145333

Using narratives to infer preferences in understanding the energy efficiency gap

Received: 16 March 2022

Tobias Wekhof^{1,2} & Sébastien Houde³

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 Check for updates

Investing in energy efficiency is crucial for a low-carbon economy, particularly in the building sector. Despite various subsidy programmes meeting energy targets is challenging because households do not invest sufficiently. Here we study the low numbers of energy efficiency retrofits carried out by homeowners. We use narratives, an emerging method based on open-ended survey responses, to identify the barriers and determinants behind renovation decisions. Using natural language processing, we transform narratives into quantifiable metrics. Whereas financial considerations are a major barrier for homeowners, their main reasons for renovating are not related to energy savings. Most homeowners delay energy-saving investments until their buildings require renovation. Co-benefits such as environmental concerns and comfort gains are equally or more important than financial motivations. Many homeowners are unaware of existing policies and would favour reducing the bureaucracy of retrofits. Subsidies, although popular, are likely to be mistargeted. Effective policies should also consider institutional factors such as the bureaucratic burden and the accessibility of information.

023-01303-x

Blasch, J. E., Filippini, M., Kumar, N., & Martinez-Cruz, A. L. (2022). Boosting the choice of energy-efficient home appliances: The effectiveness of two types of decision support. *Applied Economics*, 54(31), 3598–3620. <https://doi.org/10.1080/00036846.2021.2014395>

Assume that you need to replace your fridge. You expect that you live in your current residence for another 10 years. In a shop you find the following two fridges which are identical in terms of size and cooling service.

	Fridge - A	Fridge - B
Purchase Price:	3300 CHF	2800 CHF
Electricity Consumption:	100 kWh/year	200 kWh/year

Assuming that one kilowatt hour (kWh) of electricity will cost about 20 Rappen on average during the next 10 years and that the value of 1 CHF in 10 years is the same as the value of 1 CHF today:

Which of the two fridges minimizes your expenditure for cooling food and beverages during the lifetime of 10 years?

- The fridge for 3300 CHF
- The fridge for 2800 CHF

Figure 1. The refrigerator question in the identification task.

cost and to distinguish them from the respondents who followed another, possibly heuristic-based, decision-making strategy.¹⁵

Descriptive statistics

This sub-section reports descriptive statistics of variables informing the econometric specifications reported in [Section IV](#). Control variables include gender, age, ownership of the house, income, and education.¹⁶ In addition, all econometric specifications also control for respondents' pre-treatment energy and investment literacy – measured by an

(i) knowledge of the average price of a kilowatt hour of electricity in Switzerland; (ii) knowledge of the usage cost of different household appliances; and (iii) knowledge of the electricity consumption of various household appliances. This index ranges from 0 to 11 in the HSEU-Bern data, and from 0 to 9 in the SHEDS data. For descriptive statistics of the single items of the index see the Appendix, [Table A3](#).¹⁷ The specifications on the HSEU-Bern data also control for pre-treatment investment literacy. INVLIT is a binary variable that takes the value one if the respondent correctly solved a compound interest rate calculation, and zero otherwise.¹⁸ Compound interest rate calcu-

Additional figures and tables

Information for appliance choice		
<h2>Which TV set is less expensive?</h2>		
	 TV set A	 TV set B
Price	800 CHF	750 CHF
Electricity consumption	50 kWh/year	150 kWh/year

(a) Slide-1

How to calculate the total cost of an electric appliance?

The total cost of an electric appliance is composed of the **price of the appliance** and its **lifetime energy cost**.

(b) Slide-2

Example calculation for TV set B		
Price of the TV set	+ Lifetime energy cost	= Total cost
750 CHF	+ 150 CHF	= 900 CHF
Yearly electricity consumption (150 kWh/year)	x Price per kWh of electricity (0.20 CHF/kWh)	x Expected lifetime (5 years)

(c) Slide-3

Information for appliance choice		
Which TV set is less expensive?		
	TV set A	TV set B
Price	800 CHF	750 CHF
Electricity consumption	50 kWh/year	150 kWh/year
	TV set A	TV set B
Price	800 CHF	750 CHF
Energy cost per year	10 CHF ($50 \text{ kWh} \times 0.20 \text{ CHF}$)	30 CHF ($150 \text{ kWh} \times 0.20 \text{ CHF}$)
Energy cost over 5 years	50 CHF	150 CHF
Total cost over 5 years	850 CHF	900 CHF

(d) Slide-4

Figure A1: Information slides as intervention for the TRSLIDE treatment group.

With this online calculator you can calculate and compare the energy costs and total costs of two different models of refrigerators. This will help you in making an informed choice between the two appliances.

You can vary the electricity price and the characteristics of the refrigerator (purchase price, electricity consumption and expected lifetime) and calculate the cost. It is assumed that a refrigerator is used 24 hours a day. For simplicity, it is also assumed that the price of electricity will remain constant and that the value of 1 CHF in 10 years is the same as the value of 1 CHF today.

Lifetime of the appliance: 10 years

Cost of 1 kWh: 20 Cents

Refrigerator A

Purchase Price: CHF 0

Electricity Consumption: 0 kWh/year

Costs for Refrigerator A

Yearly Energy Cost: CHF 0

Total Energy Cost: CHF 0
over appliance lifetime

Total Cost: CHF 0
purchase price + total energy costs

Refrigerator B

Purchase Price: CHF 0

Electricity Consumption: 0 kWh/year

Costs for Refrigerator B

Yearly Energy Cost: CHF 0

Total Energy Cost: CHF 0
over appliance lifetime

Total Cost: CHF 0
purchase price + total energy costs

* Note that java needs to be enabled within your browser to see the calculator on this page. If you are unable to see or use the calculator above, you can still return and continue with the survey as usual.

Figure A2: Online calculator as intervention to the TRCALC treatment group.

In the following, we will ask you to make a choice between two electrical appliances.

To support your decision we provide some information helping you to make an informed choice that considers the total cost of the appliances.



Fig. 1. An example of the categorical and continuous-scale label.

Figure 13: 1743737229948

Herrmann, M. R., Brumby, D. P., Oreszczyn, T., & Gilbert, X. M. P. (2018). Does data visualization affect users' understanding of electricity consumption? *Building Research &*

Does data visualization affect users' understanding of electricity consumption?

Melanie R. Herrmann ^a, Duncan P. Brumby ^a, Tadj Oreszczyn ^b

^aUCL Interaction Centre, Department of Computer Science, University College London, London, UK; ^bGrantham Institute, Imperial College London, London, UK

ABSTRACT

Different data visualizations are investigated for how they enable users to understand their domestic energy consumption. Smart metering can potentially enable users to change their behaviour and save energy. However, concerns exist about how well users understand domestic energy feedback. Two challenges are addressed. First, aggregate consumption values typically show aggregate consumption and they show time-series data that are difficult to relate to everyday actions in the household. A laboratory study assessed changes in participants' knowledge of how much electricity they used after being exposed to different forms of energy-consumption data: (1) an aggregated time-series line graph, (2) a disaggregated time-series line graph, and (3) a normalized disaggregated visualization that deemphasized time. Participants in the study were asked to play a game both before and after they saw the simulation. Participants in the game were more accurate and more confident in their post-test judgments about everyday electricity consumption than other participants. These findings suggest that the way energy-consumption data are presented affects users' understanding of domestic electricity consumption. Future work should investigate how disaggregated energy feedback at the appliance level should be presented to different generations of technology.

Which one of the two activities consumes more electricity?



making coffee

(15 minutes)



running the
dishwasher
(1 hour 30 minutes)



(2 minutes)



(1 hour 30
minutes)



(15 minutes)



(1 hour 30
minutes)



(2 minutes)



(1 hour)



(30 minutes)



(2 minutes)



(1 hour)

How confident are you?

Low

1 2 3 4 5 High

CONTINUE

CONTINUE

Figure 3. Simulation.

Kanay, A., Hilton, D., Charalambides, L., Corrégé, J.-B., Inaudi, E., Waroquier, L., & Cézéra, S. (2021). Making the carbon basket count: Goal setting promotes sustainable consumption in a simulated online supermarket. *Journal of Economic Psychology*, 83, 102348. <https://doi.org/10.1016/j.jeop.2020.102348>

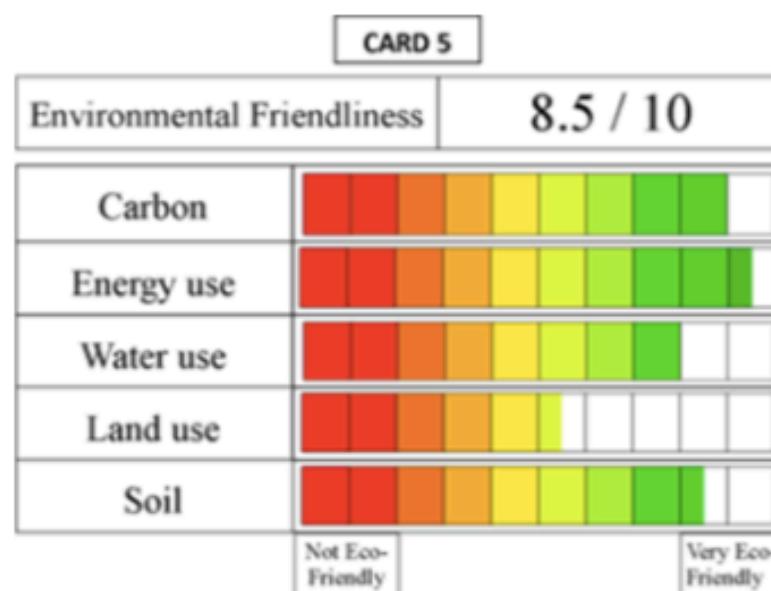


Fig. 5. Label selected as the most effective in communicating the eco-friendliness of a product ([Vlaeminck et al., 2014, p.182](#)).

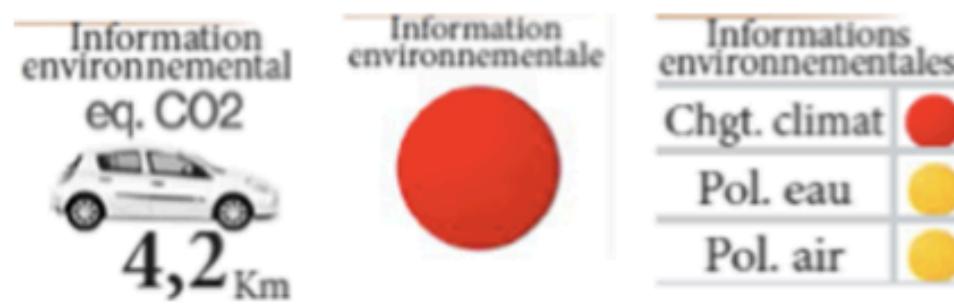


Fig. 6. Kilometric Environmental Label (label on the left), Single Traffic Lights Environmental Label (label in the middle), Multiple Traffic Lights Environmental Label (label on the right) ([Muller et al., 2019](#)).

basket-level compensations between high carbon footprint products and low ones. In particular, as inter-categorical comparisons in decision-making are likely to require greater cognitive effort than intra-categorical choice processes ([Abelson & Levi, 1985; Payne et al., 1993](#)), we assume that basket level representations may facilitate greater recognition of inter-categorical differences in product carbon footprint and hence reduction of basket carbon footprint through inter-categorical substitutions (e.g., vegetable for meat products).

As the presentation format of information has an impact on the choice of information processing strategy ([Bettman & Kakkar, 1977](#)), we tested different feedback formats such as numerical format, bi-colour graphical and multi-colour graphical forms. While numerical feedback can be shown effective in changing behaviour in the sustainability context (e.g., [Perino et al., 2014](#)), graphical presentation of information can be even more effective. [Garcia-Retamero and Cokely \(2013\)](#) emphasized the importance of properly-designed visual aids in communicating risk information. For instance, [Garcia-Retamero and Galesic \(2010\)](#) demonstrated that numerical information coupled with visual aids such as icon arrays and bar graphs, improved medical decision-making. Similarly, [Garcia-Retamero and Hoffrage \(2013\)](#) showed that information presented in a numerical format accompanied with visual aids lead to better diagnostic inferences compared to the case when information was presented only in a numerical format. Another study conducted by [Walker, Stange, Dixon, Koehler and Fugelsang \(2019\)](#) showed that gambling related judgments were improved when payback percentage was presented in a graphic format instead of a numerical one.

By orienting consumers to buy sustainable baskets, we expect the cognitive dynamics of consumer behaviour to be modified in a number of potentially important ways. First, the basket format allows consumers to compare the environmental impact of different food categories and recognize that certain food categories (e.g., meat and dairy) have much higher carbon footprints than others (e.g., fruit and vegetables). In addition, giving consumers precise feedback about the environmental impact of each item that they put into their basket may enable learning and hence the acquisition of accurate mental representations of product carbon footprint that may

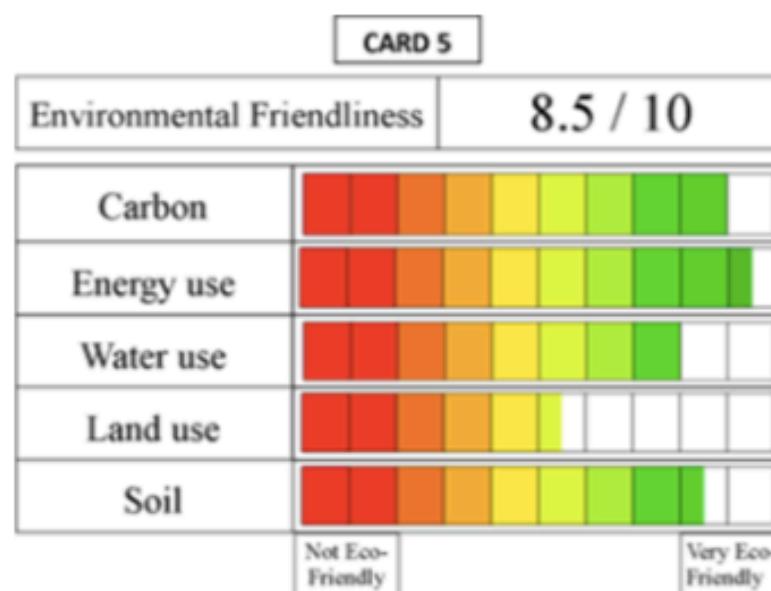


Fig. 5. Label selected as the most effective in communicating the eco-friendliness of a product ([Vlaeminck et al., 2014, p.182](#)).

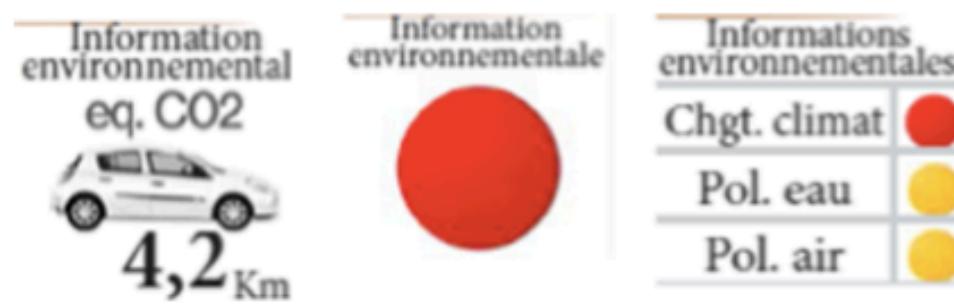


Fig. 6. Kilometric Environmental Label (label on the left), Single Traffic Lights Environmental Label (label in the middle), Multiple Traffic Lights Environmental Label (label on the right) ([Muller et al., 2019](#)).

basket-level compensations between high carbon footprint products and low ones. In particular, as inter-categorical comparisons in decision-making are likely to require greater cognitive effort than intra-categorical choice processes ([Abelson & Levi, 1985; Payne et al., 1993](#)), we assume that basket level representations may facilitate greater recognition of inter-categorical differences in product carbon footprint and hence reduction of basket carbon footprint through inter-categorical substitutions (e.g., vegetable for meat products).

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The current U.S. fuel economy label for automobiles (revised in 2013) includes a number of metrics associated with energy. The familiar MPG metric is most prominent, but one can also see gallons per 100 miles (GPHM), annual fuel cost, a rating of greenhouse gas emissions, and a five-year relative cost or savings figure compared with what one would spend with an average vehicle (see Figure 1). The original label introduced in the 1970s contained two MPG figures (see Figure 2). As the label was being redesigned for 2013, there was praise for including new information and criticism for providing too much information.⁵⁻⁷ The new fuel economy label raises two general questions that apply to many settings in which consumers are informed about energy use, such as on appliance labels, smart meter feedback, and home energy ratings:

- What energy information should be given to consumers?
- How much is the right amount?

How information is presented always matters. More often than not, people pay attention to what they see

trapped with a poor understanding of the true consequences of their decisions. But this important communication can be improved.

A CORE Approach to Better Decisionmaking

How people learn and how they make decisions is less of a mystery than ever before. Insights from psychology, specifically, are now used to help consumers make better decisions for themselves and for society.^{9,10} In this context, we have created four research-based principles, which we abbreviate as CORE, that could be employed to better educate people about energy use and better prepare them to make informed decisions in that domain. They include:

- CONSUMPTION: Provide consumption rather than efficiency information.
- OBJECTIVES: Link energy-related information to objectives that people value.
- RELATIVE: Express information relative to meaningful comparisons.
- EXPAND: Provide information on expanded scales.

Figure 1. Revised fuel economy label (2013)



Figure 2. Original fuel economy label (from 1993)

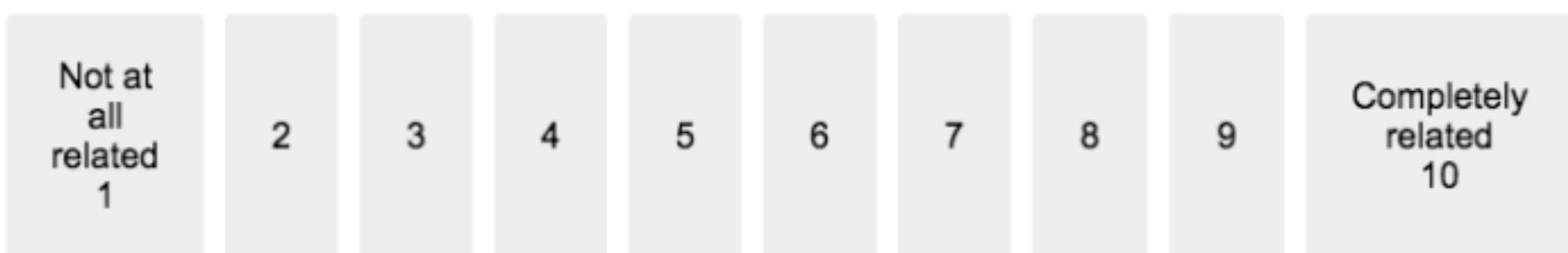


Ungemach, C., Camilleri, A. R., Johnson, E. J., Larrick, R. P., & Weber, E. U. (2018). Translated Attributes as Choice Architecture: Aligning Objectives and Choices Through Decision Signposts. *Management Science*, 64(5), 2445–2459. <https://doi.org/10.1287/mnsc.2016.2703>

Two things are considered "related" if one changes at the same time as the other. For example, two metrics would be completely unrelated if, as one changes, the other does not change. On the other hand, two metrics would be completely related if, as one changes, the other perfectly matches it. There are also varying degrees of relatedness between these two points.

The direction of the changes does not need to be the same. For example, as you *increase* the amount of water flow into a bathtub, the water level *increases* and the amount of empty tub space *decreases*. Thus, bath water flow, water level, and empty space are all strongly related.

How related are Annual Fuel Cost and Greenhouse Gas Rating?



Imagine that you were shown four fuel economy labels that had the Annual Fuel Costs (AFC) shown on the left hand column. What do you think the associated Greenhouse Gas Ratings (GGR) would be for each of these four fuel economy labels?

	GGR = 1	GGR = 2	GGR = 3	GGR = 4	GGR = 5	GGR = 6	GGR = 7	GGR = 8	GGR = 9	GGR = 10
AFC = \$3,800	<input type="radio"/>									
AFC = \$2,150	<input type="radio"/>									
AFC = \$2,900	<input type="radio"/>									
AFC = \$1,650	<input type="radio"/>									

Figure 14: 1743737396332

2.1.3 | Judgment task

In each trial, participants were presented information about a consumer product (primarily electronic devices, e.g., a washing machine) and were asked to rate the product's attractiveness ('Based on the information above, how attractive is this product to you?' on a 7-point scale from 0 = 'not at all attractive' to 6 = 'extremely attractive'). For each product, a picture of a typical model was displayed; below it, information about three product attributes (e.g., energy efficiency; see Figure 1) was available. In the *numbers-only* condition, numeric values were provided for each attribute. The numeric values were specific to the attributes and varied across units, ranging from fairly interpretable ratings (e.g., '4 out of 5 stars') to technical details (e.g., '400 kWh/year'). In the *numbers-and-labels* condition, verbal labels were also available that evaluated the numeric value (e.g., '400 kWh/year' was 'fair' and '4 out of 5 stars' was 'good') and resembled those provided by product-comparison and product-rating homepages such as Consumer Reports. Participants did not receive prior information on the products, attributes, or value ranges, although we provided the general range of evaluative categories and explanations of the less familiar attributes.

On each trial, each piece of product information (including the picture) was hidden behind boxes and could be opened by hovering the mouse cursor over the box. At the bottom of the trial page, participants were asked to answer the attractiveness question.

2.1.4 | Stimuli

Based on thorough online research, we selected a range of relevant attributes for each product. In a pretest with 50 participants, we tested these attributes for their importance when evaluating the product. For each product, we chose the attribute rated most important as the first attribute (i.e., the varied attribute) and the two less important ones as second and third attributes (i.e., fixed attributes). For each of the three attributes, based on further online research, we carefully selected a numerical value corresponding to each of the five verbal label values (i.e., 'bad', 'mediocre', 'fair', 'good', and 'excellent'). For the variable attribute, the three levels were selected from the 'bad', 'fair', and 'excellent' levels, including respective numeric values. The numeric values and verbal labels for the second and third attributes as well as all attributes of the filler trials were selected from the three intermediate levels (i.e., 'mediocre', 'fair', or 'good') to avoid effects of extreme values.

(a)

Please consider this electric bike:

	Product Picture
	Numeric value
Battery power	800 Wh
Number of gears	Value
Weight	Value

(b)

Please consider this electric bike:

		
	Numeric value	Verbal label
Battery power	800 Wh	excellent
Number of gears	3	mediocre
Weight	50 lbs.	fair

FIGURE 1 Study 1: Example (a) of the numbers-only condition, with one opened box as in the experiment, and (b) of the numbers-and-labels condition with all boxes opened to display all possible

Figure 15: 1743737414919

FIGURE 3 Studies 2a and 2b:
Examples of (a) the numbers-only-condition, with one opened box mirroring what participants saw in the experiment, and (b) the numbers-and-labels condition with all boxes opened to display all possible values (participants could only open one box at a time)

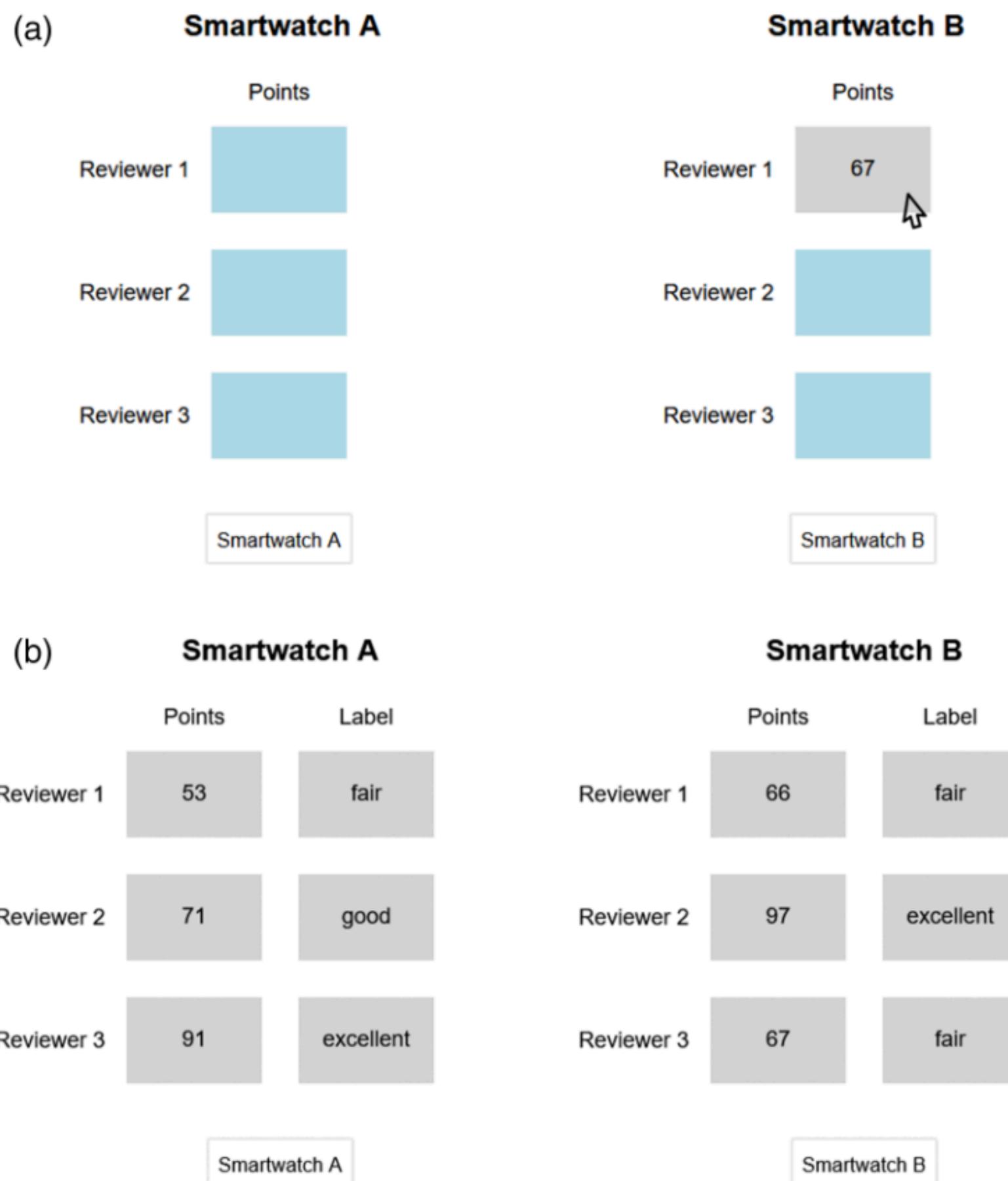


Figure 16: 1743737417934



Looking beyond time preference: Testing potential causes of low willingness to pay for fuel economy improvements

Féidhlim P. McGowan ^{a,b,*}, Eleanor Denny ^b, Peter D. Lunn ^{b,c}

^a J.E Cairnes School of Business and Economics, University of Galway, Galway, Ireland

^b Behavioural Research Unit, Economic and Social Research Institute, Dublin, Ireland

^c Department of Economics, Trinity College Dublin, Ireland

ARTICLE INFO

Dataset link: <https://osf.io/73psm/>

Keywords:

Energy-efficiency gap
Experiment
Willingness-to-pay
Underestimation bias
Concentration bias
Discounting

ABSTRACT

Time preferences are considered a leading cause of the energy efficiency gap. We test two cognition-based mechanisms (concentration bias and underestimation bias) which are distinct from time preferences but can produce identical behaviour when costs are paid upfront and benefits are spread over time. We use an experiment that measures willingness-to-pay for an improvement in fuel economy to test the explanatory power of these mechanisms. The sample is large, nationally representative and comprised only of car buyers ($n = 2368$). The experiment varies between-subjects (i) the payment schedule for the fuel economy improvement, and (ii) the temporal framing of its monetary benefit. We combine the payment schedules and the benefit frames so that the pattern of results predicted by time preferences differs from the pattern predicted by cognitive mechanisms. Results support the preregistered hypotheses: willingness-to-pay increases as the payment schedule becomes more dispersed across time and decreases when the benefit is presented as more disaggregated (i.e. a monthly saving instead of annual or multi-year saving). The findings are consistent with the predictions of the two cognitive mechanisms, which may explain part of the energy-efficiency gap currently attributed to pure time preference.

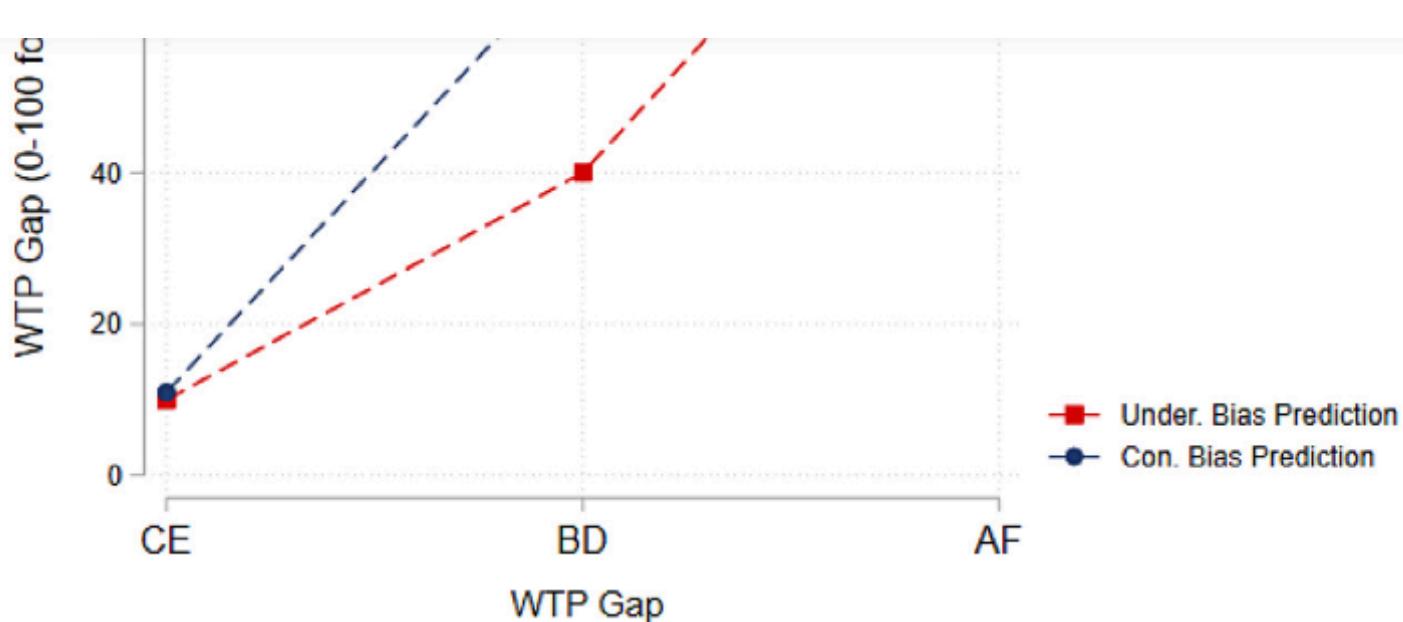


Fig. 1. Graphical Illustration of opposing predictions of Concentration Bias and Underestimation Bias regarding size of intermediate WTP gap BD relative largest gap, AF, and smallest gap, CE.

Annual Running Cost by Journey Type for A and B					
Short Drives (less than 30mins)		Medium Drives (30mins – 1hr)		Longer Drives (1hr+)	
A	B	A	B	A	B
€252	€192	€432	€348	€576	€468

Annual Running Cost by Journey Type for A and B					
Short Drives (less than 30mins)		Medium Drives (30mins – 1hr)		Longer Drives (1hr+)	
A	B	A	B	A	B
€192	€192	€324	€324	€744	€492

Fig. 2. Dispersed vs. concentrated fuel cost savings in low accessibility condition. Both savings are €252 per year.

Annual Running Cost by Journey Type for A and B					
Short Drives (less than 30mins)		Medium Drives (30mins – 1hr)		Longer Drives (1hr+)	
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A	B	A	B	A	B
€192	€192	€324	€324	€744	€492

Annual Savings from B:	€60	€84	€108		
Annual Savings from B:					

Fig. 3. Dispersed vs. concentrated savings in high accessibility condition where cost difference is explicit. Both savings are €252 per year.



Which electric vehicle charging station to upgrade? Biased judgments based on differences in station efficiency

Ola Svenson ^{a,b,*}, Ilkka Salo ^c, Inés Duce Gimeno ^{a,d}

^a Department of Psychology, Stockholm University, Stockholm, Sweden

^b Decision Research, Oregon Research Institute, Oregon, USA

^c Department of Psychology, Lund University, Lund, Sweden

^d Department of Psychology, Universidad Autónoma de Madrid, Madrid, Spain

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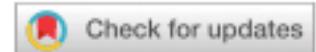
ABSTRACT

One way of controlling global warming is to substitute fuel driven cars with electric cars. Electric vehicles need to be charged. For maximal efficiency the charging times should be as short as possible. In the US charging stations are classified as Level 1 charging 5–10 miles/h, Level 2 25 miles/h and Fast DCFC stations 150–1000 miles/h. We asked participants to select one of two upgrades of charging stations that would save most charging time for a vehicle. The alternatives were upgrading L1 (5miles/h) to L2 (25 miles/h) or L2 (25miles/h) to Fast (250 miles/h). In all, 86% of the participants wanted to upgrade to a Fast station, which objectively saves less time than L1 to L2. The second study replicated the first study and 91% of the participants wanted to upgrade to the Fast (250) station. The third study offered alternatives with smaller objective efficiency differences than the earlier studies: upgrading L2 (30) to Fast (150) and Fast (150) to Fast (600) and 68% of the participants preferred the second incorrect alternative. Verbal justifications showed that many participants seemed to assume that differences in charging time are proportional to charging time saved. The results have practical implications and illustrate the difficulty to process reciprocal variables leading to incorrect decisions. Finally, we suggest two strategies for counteracting biased intuitive decision making when charging efficiencies are compared.

Figure 17: 1743737451456

Herberz, M., Hahnel, U. J. J., & Brosch, T. (2022). Counteracting electric vehicle range concern with a scalable behavioural intervention. *Nature Energy*, 7(6), 503–510.

<https://doi.org/10.1038/s41560-022-01028-3>



Counteracting electric vehicle range concern with a scalable behavioural intervention

Mario Herberz , Ulf J. J. Hahnel and Tobias Brosch

All-electric vehicles remain far from reaching the market share required to meaningfully reduce transportation-related CO₂ emissions. While financial and technological adoption barriers are increasingly being removed, psychological barriers remain insufficiently addressed. Here we show that car owners systematically underestimate the compatibility of available battery ranges with their annual mobility needs and that this underestimation is associated with increased demand for long battery ranges and reduced willingness to adopt electric vehicles. We tested a simple intervention to counteract this bias: providing tailored compatibility information reduced range concern and increased willingness to pay for electric vehicles with battery ranges between 60 and 240 miles, relative to a 50-mile-range baseline model. Compatibility information more strongly increased willingness to pay than did information about easy access to charging infrastructure, and it selectively increased willingness to pay for car owners who would derive greater financial benefits from adopting an electric vehicle. This scalable intervention may complement classical policy approaches to promote the electrification of mobility.

The adoption of battery electric vehicles (BEVs) is speeding up in many countries, which is an important step towards curbing the nearly 18% share of global CO₂ emissions currently accounted for by road traffic^{1,2}. Increased adoption can be ascribed to a range of policies that aim to promote BEV adoption. Current policies are mainly based on providing financial incentives, creating a denser charging infrastructure and adapting traffic regulations, for instance, by providing privileged access to public transport lanes³. In particular, subsidies of BEV purchase prices have been shown to successfully counteract consumer tendencies to excessively weigh the higher BEV upfront costs and to discount future financial benefits⁴.

Despite these achievements, the global share of BEVs is still far from its mass market objective. In 2020, electric vehicles (including hybrid-electric vehicles) accounted for only 1% of the global car stock, requiring almost exponential growth of sales to reach the 12% sustainable development target in 2030⁵. Concerns have been raised that financial incentives and technological improvements may be insufficient to convince the majority of hesitant consumers^{6–8}. For example, financial incentives do not always increase BEV adoption, suggesting that other, non-financial factors may play a crucial role⁹. Similarly, recent research suggests that introducing a tax for CO₂

Given that many financial and technological barriers are already being alleviated in many countries³, behavioural interventions based on insights from psychology may complement the existing policies in the promotion of BEV adoption¹⁰. Many consumers are sceptical that the available BEV battery ranges can meet their mobility needs. Range concern—the worry that a given battery range will be insufficient to reach one's destination—is one of the major barriers to BEV adoption^{6,8,17,18}. Consequently, consumers express strong preferences for long battery ranges¹⁹ and require considerable range safety buffers to feel comfortable driving a BEV^{20,21}. Indeed, the perceived compatibility of a given BEV with individual mobility needs and lifestyles seems to be one of the most important predictors of BEV purchase intentions and adoption^{22–25}.

Analyses of actual driving profiles, on the other hand, suggest that even BEVs with moderate battery ranges already meet most consumers' mobility needs⁶. Across Australia, China, the United States and European countries, research has found that more than 90% of individual mobility needs can be met with available and increasingly affordable BEV battery ranges such as 200 km^{18,26–29}. Despite the scientific consensus that subjectively insufficient battery ranges constitute a barrier to BEV adoption^{6,8,17,18}, previous behav-

Figure 18: 1743737463504

Biswas, S., Fuentes, T. L., McCord, K. H., Rackley, A. L. S., & Antonopoulos, C. A. (2024). Decisions and decision-makers: Mapping the sociotechnical cognition behind home energy upgrades in the United States. *Energy Research & Social Science*, 109, 103411. <https://doi.org/10.1016/j.erss.2024.103411>

Home energy upgrade decisions, such as adopting energy efficient equipment/appliances and renewable energy, are embedded within broader decisions and actions for upgrading the home. In this paper, 121 households in four states were interviewed to investigate the cognitive process of decision-making for home upgrades at the intersection of individual self-identities, normative goals of households and their sociotechnical environment. We found that home upgrades occur typically as interconnected sets of projects. They are constituted of decision dilemmas between domestic space-making aspirations and technological choices, moderated by sentiments, opinions of peers, information, limiting factors and self-identities. Indoor upgrades are largely influenced by the functional and emotional goals of the household, whereas exterior and structurally complex upgrades are usually determined by parameters of the sociotechnical environment, including costs and available expertise. Behaviorally, functional needs and social situation of individuals are more influential to upgrade decisions than environmental values or ideological positions on decarbonization.

He, G., Hemmer, P., Vössing, M., Schemmer, M., & Gadira, U. (2025). Fine-Grained Appropriate Reliance: Human-AI Collaboration with a Multi-Step Transparent Decision Workflow for Complex Task Decomposition (No. arXiv:2501.10909). arXiv. <https://doi.org/10.48550/arXiv.2501.10909>

Fine-Grained Appropriate Reliance: Human-AI Collaboration with a Multi-Step Transparent Decision Workflow for Complex Task Decomposition

GAOLE HE, Delft University of Technology, The Netherlands

PATRICK HEMMER, Karlsruhe Institute of Technology, Germany

MICHAEL VÖSSING, Karlsruhe Institute of Technology, Germany

MAX SCHEMMER, Karlsruhe Institute of Technology, Germany

UJWAL GADIRAJU, Delft University of Technology, The Netherlands

In recent years, the rapid development of AI systems has brought about the benefits of intelligent services but also concerns about security and reliability. By fostering appropriate user reliance on an AI system, both complementary team performance and reduced human workload can be achieved. Previous empirical studies have extensively analyzed the impact of factors ranging from task, system, and human behavior on user trust and appropriate reliance in the context of one-step decision making. However, user reliance on AI systems in tasks with complex semantics that require multi-step workflows remains under-explored. Inspired by recent work on task decomposition with large language models, we propose to investigate the impact of a novel Multi-Step Transparent (MST) decision workflow on user reliance behaviors. We conducted an empirical study ($N = 233$) of AI-assisted decision making in composite fact-checking tasks (*i.e.*, fact-checking tasks that entail multiple sub-fact verification steps). Our findings demonstrate that human-AI collaboration with an MST decision workflow can outperform one-step collaboration in specific contexts (*e.g.*, when advice from an AI system is misleading). Further analysis of the appropriate reliance at fine-grained levels indicates that an MST decision workflow can be effective when users demonstrate a relatively high consideration of the intermediate steps. Our work highlights that there is no one-size-fits-all decision workflow that can help obtain optimal human-AI collaboration. Our insights help deepen the understanding of the role of decision workflows in facilitating appropriate reliance. We synthesize important implications for designing effective means to facilitate appropriate reliance on AI systems in composite tasks, positioning opportunities for the human-centered AI and broader HCI communities.

CCS Concepts: • **Human-centered computing → Empirical studies in HCI.**

Additional Key Words and Phrases: Human-AI Collaboration, Mutli-step Decision Workflow, Transparency, Appropriate Reliance

Figure 19: 1743737498528

12/16/24

llm as information source (vs. tables, graphs, web-search etc.) - e.g, how well participants perform in some decision task when we manipulate their resource. llm as a feedback mechanism - explain how to perform better in natural language. - compared against numerical accuracy score, reinforcement feedback, no feedback etc.

12/10/24

Participants need to make energy reduction plans, but must first ‘search’ for relevant information - by checking on appliance usage, aggregate electricity usage etc.

Study ideas

<https://gemini.google.com/app/1618628a009fdfed>

Here are some cognitive psychology experiment study ideas involving human interaction with LLMs and energy-related decision-making, based on the provided document:

Participant as Advisor, AI as Client

- **Advising an LLM Client:** Have the participant take on the role of an energy advisor. Their task is to convince an LLM, acting as the client, how to change its current (simulated) behavior to reduce energy use most effectively. You could manipulate the LLM client’s characteristics (*e.g.*, receptiveness to advice, stated budget constraints, lifestyle) and measure the participant’s advising strategies and effectiveness.
- **Collaborative Planning with AI Assistant:** The participant acts as an energy advisor but works with an LLM assistant to create energy plans for clients (who could be hypothetical or simulated). The study could manipulate the quality of the LLM assistant’s plans (*e.g.*, consistently good vs. inconsistent/poor). Measures could include the quality of the final plan, participant satisfaction, and how participants decide to use or override the LLM assistant’s help.
- **LLM-Mediated Information Seeking:** Participants perform an energy planning task and can interact with an LLM chatbot to ask questions about appliance usage, energy units, or saving tips. The study could examine how the availability of this LLM resource influences planning accuracy and strategy, particularly when the initial energy reduction goals are presented in different formats (like kWh, \$, or %)

AI as Client & AI as Planner/Advisor (with Participant Interaction)

- **Comparing Plans:** Participants create their own energy reduction plan for a given scenario[cite: 296, 425]. They are then presented with an alternative plan generated by an LLM planner[cite: 296]. Participants must choose which plan to implement (their own or the LLM's) or perhaps integrate aspects of both[cite: 296, 425]. This setup allows investigation into factors influencing trust, perceived competence of the AI, and potential over/under-reliance[cite: 426, 428]. The complexity of the planning problem or the manipulated quality/bias of the AI's plan could be varied[cite: 296].
- **Collaborative Planning with LLM Partner:** Pair a human participant with an LLM agent to collaboratively create an energy plan[cite: 339, 340, 341]. The LLM could offer suggestions, ask clarifying questions, or present information in different formats to assist the human[cite: 340, 343]. Analyzing the interaction dynamics and the final plan's quality could reveal how different information formats are utilized in collaboration and the LLM's effectiveness as a planning tool[cite: 344, 345, 346].
- **Multi-Step Workflow with LLM:** Use a more complex task, like composite fact-checking related to energy claims, where participants work with an LLM through a multi-step workflow[cite: 278, 279, 280]. This allows examining appropriate reliance at a finer granularity, assessing how users interact with intermediate LLM steps versus just a final output[cite: 281, 282]. This could be adapted to energy planning by breaking the planning down into sub-goals or stages where LLM assistance is provided.

III. Understanding Cognitive Representations

- **Identifying Dimensions:** Present energy data in various formats (tables, graphs)[cite: 429]. Ask participants to identify key dimensions (e.g., appliance, time) and weight their importance[cite: 430, 431]. This probes mental models of energy consumption[cite: 433, 434].
- **Abstraction Levels:** Ask participants to create energy plans at different levels: concrete (specific kWh per appliance) versus abstract (target temperatures, usage hours)[cite: 435, 436]. Measure time, difficulty, and plan quality to understand hierarchical reasoning in this context[cite: 437, 438, 439].
- **LLM Analysis of Reasoning:** After a planning task, ask participants to explain their strategies in writing[cite: 403]. Use an LLM to analyze these explanations for themes, difficulties, and strategy differences related to how the task information was presented (e.g., goal in kWh vs. % vs. USD)[cite: 404, 405, 406, 407, 408, 409, 410].

Study ideas

Function learning or judgement paradigm - with household appliances. Learning some general principles about how much energy items use, and then testing on novel objects - manipulate direct energy judgements vs. money saving. - before or after the utility planning task?

Connect to literature on forecasting?

Simulating the existing representation study manipulations with LLM's - Then seeing how different prompts or framing influence performance

Studying what representations people use when thinking about energy - The dimensions of a heating bill - The dimensions (and weights) of electricity from appliances

Task of listing as many things as possible that someone could do to reduce their energy bill - with AI assistance, or without

Participant takes the role of energy advisor - convincing llm client how to reduce their energy use

Participant takes the role of energy advisor - working with an llm assistant to create energy plans for clients - Some llm assistants create really good plans, others don't - Using the llm to decide how best to help the client

Reward function that's optimized within certain bounds of appliance type use (e.g., if heat goes too low, reward plummets)

Plans at different layers of abstraction - setting kwh per appliance - explicitly setting temperature average, and appliance hour usage amounts

The problem of creating a plan to influence some variable (e.g., utility bill) - identifying the relevant dimensions - Assigning weight to the dimensions

Ability to adjust plans based on added context. - e.g., the Meyers family wants to keep their energy bill the same -but Mr. Meyer needs to start working from home - and will need to use more energy to run his power tools. Make adjustments to their plan that will accomodate this change - while also maintaining their current energy costs.

Ways of integrating AI into a study on energy use

- Participant plays role of advisor, tells 'AI client' how to most effectively change current behavior
 - AI generated feedback on advice?
- Participants choose between their own plan, and an AI's alternative plan
 - Manipulate what type of energy plan problems AI's are good for
 - Assess overreliance/underreliance tendencies
 - Whether the tendency to over or under rely depends on complexity of problem

Things a LLM could do in the context of an experimental psychology task? - Custom feedback - summarize (and critique) user response patterns at trial or block level

NB_LLM-2

Building upon the original study that investigated the impact of presenting energy reduction goals in different numerical formats (kWh, %, USD) on consumers' planning accuracy, several compelling follow-up studies could incorporate a Large Language Model (LLM) component to further explore this complex interplay between information format, cognitive processing, and energy-related decision-making. These studies could leverage the unique capabilities of LLMs in simulating human behavior, generating diverse content, providing personalized feedback, and analyzing textual data, thereby offering novel insights that complement and extend findings from human-only studies.

1. LLM as a Simulated Participant with Varying Energy Literacy:

A follow-up study could involve creating LLM-powered agents designed to simulate consumers with different levels of energy literacy. These agents could be prompted with the same energy reduction planning tasks presented in kWh, percentages, or USD, mirroring the original study's design. The prompts for the LLM agents could be carefully crafted to embody characteristics of individuals with low, medium, and high energy literacy, potentially drawing upon existing definitions and measures of energy literacy.

- **Methodology:** Develop distinct prompt sets for LLM agents representing different energy literacy levels. These prompts might include information about their understanding of energy units, typical household behaviors, and their tendency to rely on different cues (e.g., absolute numbers, relative changes, monetary costs). Present these simulated agents with the energy planning task using the three different formats (kWh, %, USD) for the reduction goal, across the same family scenarios (climate regions) as the original study. Record the energy allocation decisions made by each LLM agent and analyze the accuracy of their plans in relation to the target reduction.
- **Comparison with Human Data:** Compare the planning accuracy of the LLM agents across the different information formats and energy literacy levels with the data obtained from human participants in the original study. This comparison could reveal whether the LLM's simulated cognitive processes align with observed human behavior and whether the effect of information format on planning accuracy is consistent across both simulated and human samples.
- **Exploring Reasoning Processes:** Unlike observing human participants' explicit reasoning, the internal processes of the LLM can be probed (to the extent allowed by the model). Analyzing the "reasoning" generated by the LLM agents (if the model provides such output) when making planning decisions in response to different formats could offer insights into the cognitive strategies employed by the simulated agents and how these strategies might be influenced by their simulated energy literacy and the presentation format.

2. LLM for Generating Explanations and Personalized Feedback:

Another avenue for follow-up research involves using an LLM to provide explanations and personalized feedback to human participants as they engage in the energy planning task. This could help elucidate why certain information formats are more or less effective and identify potential interventions to improve planning accuracy.

- **Methodology:** Replicate the original study with human participants. However, after participants complete their initial energy allocation, introduce an LLM-powered conversational agent. This agent could ask participants to explain their planning strategies for each scenario and the rationale behind their allocation choices, particularly in relation to the presented reduction goal format. The LLM could then provide personalized feedback based on the accuracy of their plan and their stated reasoning, highlighting potential discrepancies or suggesting alternative approaches. The feedback could be tailored to the information format the participant initially received (e.g., if the goal was in %, the feedback might reframe aspects in kWh or USD to enhance understanding).
- **Analyzing Qualitative Explanations:** The LLM could be used to analyze the qualitative explanations provided by participants regarding their planning processes. Using techniques like topic modeling or sentiment analysis, the LLM could identify common themes, difficulties encountered with specific formats, and the types of reasoning employed. This analysis could provide a richer understanding of the cognitive challenges associated with each information format.
- **Impact of Personalized Feedback:** Assess whether receiving personalized feedback from the LLM, especially when information is reframed in a different format or linked to energy literacy concepts, improves participants' subsequent planning accuracy in a second planning task or in follow-up assessments. This could shed light on the potential of LLM-driven interventions for enhancing energy literacy and improving planning skills.

3. LLM for Prompt Engineering and Design of Information Displays:

LLMs could also be employed to explore more nuanced ways of presenting energy information within each format. Rather than simply providing the numerical goal, the LLM could be tasked with generating different phrasings, visual aids (if the study interface allows), or contextual information associated with each format to see if these variations impact planning accuracy.

- **Methodology:** Utilize an LLM to generate multiple variations of how the energy reduction goal could be presented within each of the three core formats (kWh, %, USD). For example, for a percentage reduction, the LLM could generate prompts that emphasize the absolute amount of energy saved, the comparison to typical household reductions, or the environmental impact of that reduction. For USD, variations could include comparisons to common household expenses or highlighting the long-term savings. Present these different variations to human participants in a controlled experiment, maintaining the overall planning task from the original study.
- **Assessing the Impact of Nuance:** Analyze whether subtle variations in the phrasing or contextualization of the energy reduction goal within each format significantly affect planning accuracy. This could help identify which specific communication strategies are most effective for conveying energy information in different units.
- **LLM-Driven Iteration:** The results from this study could then be fed back into the LLM, prompting it to generate further refined versions of the information displays based on what proved most effective. This iterative process could lead to the identification of optimized communication strategies for different energy information formats.

4. LLM for Simulating Long-Term Planning and Behavioral Change:

The original study focused on a single instance of energy planning. Follow-up studies could use LLMs to simulate how individuals might approach energy planning over time, incorporating elements of feedback, goal adjustment, and the potential for behavioral change.

- **Methodology:** Develop a simulated environment where LLM agents (again, potentially with varying simulated energy literacy) engage in repeated energy planning tasks over a simulated period (e.g., monthly or seasonal). Introduce feedback mechanisms, where the LLM agents receive information about their simulated energy consumption and the accuracy of their previous plans. Allow the agents to adjust their planning strategies and goals over time, influenced by the feedback and the format in which the information is presented.
- **Longitudinal Analysis:** Analyze how the planning accuracy and simulated energy consumption behaviors of the LLM agents evolve over the simulated period under different information formats. This could provide insights into the long-term effectiveness of each format for promoting sustained and accurate energy planning.
- **Integration with Human Data on Behavioral Change:** While direct comparison might be challenging, insights from this LLM-based simulation could be compared with findings from longitudinal studies of human energy consumption and response to feedback, helping to identify potential patterns and long-term effects associated with different information formats.

5. Combining LLMs and Human Participants in Collaborative Planning:

A novel approach could involve pairing human participants with an LLM agent to engage in a collaborative energy planning task. The LLM agent could be designed to offer suggestions, ask clarifying questions, and provide information in different formats to the human participant.

- **Methodology:** Recruit pairs of participants (or individual participants who interact with an LLM agent). Present them with an energy reduction goal and the household scenarios. Allow them to communicate and collaboratively develop an energy plan. The LLM agent could be programmed to strategically present energy information in different formats (e.g., if the human is struggling with percentages, the LLM could rephrase the information in kWh) and observe the impact on the collaborative planning process and the final accuracy of the plan.
- **Analyzing Interaction Dynamics:** Analyze the dialogue between the human participant and the LLM agent to understand how the different information formats are discussed, interpreted, and utilized in the collaborative process. This could reveal which formats facilitate clearer communication and understanding.

- **Assessing the LLM's Role as an Educational Tool:** Evaluate the LLM's effectiveness as a supportive tool for energy planning, particularly in helping individuals overcome challenges associated with specific information formats and improve their understanding of energy concepts.

Ethical Considerations:

When incorporating LLMs into studies involving human subjects, it is crucial to address ethical considerations. Participants should be informed about the use of AI agents, and their data privacy and confidentiality must be protected. The potential for bias in LLM outputs should also be acknowledged and mitigated through careful prompt design and evaluation.

By integrating LLMs into follow-up studies, researchers can gain deeper and more multifaceted insights into how the format of energy information affects consumers' planning accuracy. These studies can move beyond simply observing outcomes to explore the underlying cognitive processes, the potential for personalized interventions, and the dynamics of long-term engagement with energy-related information, ultimately contributing to the development of more effective strategies for promoting residential energy conservation.

NB_LLM-1

<https://notebooklm.google.com/notebook/b9b3533c-ddc0-49e3-b438-9e1f05272f9e?pli=1>

Suggest possible follow up studies, which investigate similar questions, but incorporate a large language model (llm) component in addition to human subjects.

Building upon the hypothetical study that examined the impact of numerical representations of energy reduction goals (kWh, %, USD) on planning accuracy, incorporating a Large Language Model (LLM) component opens several exciting avenues for future research. These studies could delve deeper into the cognitive processes involved in energy planning, explore personalized information delivery, and enhance the ecological validity of the research. Here are some possible follow-up studies:

1. Investigating LLM-Mediated Information Seeking and Planning:

- **Study Design:** Replicate the original study's design, but allow participants in all conditions to interact with an LLM-powered chatbot during the planning task. The chatbot could be designed to answer questions about appliance energy consumption, clarify the meaning of different units (kWh, %, USD), or provide general energy-saving tips.
- **LLM Functionality:** The chatbot's responses could be tailored to the information format the participant is currently working with. For example, if a participant is in the percentage condition and asks about an appliance's energy use, the chatbot could provide an estimate in terms of percentage of total household consumption or, if asked directly, in kWh. The interaction logs with the chatbot would be recorded.
- **Research Questions:**
 - Does the availability of an LLM-powered information resource mediate the effect of information format on planning accuracy? For instance, do participants in the percentage or USD conditions who utilize the chatbot more effectively achieve higher accuracy?
 - What types of questions do participants ask the chatbot in each information format condition? Do the questions reveal different levels of understanding or different cognitive challenges associated with each format?
 - Can the LLM identify common misconceptions or errors in participants' planning strategies based on their queries?
 - Does interacting with an LLM influence participants' perceived difficulty of the planning task or their confidence in their plan?
- **Connection to Sources:** This design aligns with research on Persuasive Conversational Agents (PCAs) for sustainability and the potential of LLMs to enhance user engagement and support decision-making. The study could also draw on work exploring user experience with LLM-based assistants. Analyzing the types of questions asked could provide insights into cognitive accessibility of different units.

2. Personalized Information Formatting with LLMs:

- **Study Design:** Begin by assessing participants' energy literacy and their preferred format for receiving energy information (e.g., through a pre-study questionnaire). Then, replicate the original planning task, but allow an LLM to dynamically adjust the format in which information is presented based on the participant's stated preferences or their demonstrated understanding during an initial planning stage (e.g., if they struggle with percentages, the LLM could offer information in kWh).
- **LLM Functionality:** The LLM would act as an adaptive interface, using natural language understanding to interpret user difficulties and employing natural language generation to present information in alternative formats. The system could track which formats are most frequently utilized or seem to correlate with improved planning.
- **Research Questions:**
 - Does providing energy information in participants' preferred format, facilitated by an LLM, lead to greater planning accuracy?
 - Can an LLM effectively identify when a participant is struggling with a particular format and suggest or switch to a more comprehensible one?
 - Do participants demonstrate improved planning accuracy over time as the LLM adapts the information format?
 - How do participants perceive an energy planning tool that personalizes information format based on their needs?
- **Connection to Sources:** This study connects to the idea of flexible program designs and personalized approaches in feedback programs. It also relates to research on cognitive fluency and how fluent framing can influence decision-making. The LLM's role in adapting information formats aligns with the concept of tailoring interventions to end-user characteristics.

3. LLM as a Simulated Household and Feedback Provider:

- **Study Design:** Human participants create an energy reduction plan (in one of the three formats). This plan is then "submitted" to an LLM that has been trained to simulate the energy consumption of a virtual household matching one of the scenarios from the original study (e.g., the Smith family in Texas). The LLM, based on its understanding of typical appliance usage and the participant's proposed plan, would then generate realistic feedback on the likely energy savings, potential challenges, or areas where the plan might be less effective.
- **LLM Functionality:** The LLM's feedback would be provided in natural language and could relate back to the original goal format (kWh, %, or USD). It could also ask clarifying questions or suggest alternative strategies. Participants would then have the opportunity to revise their plan based on the LLM's feedback.
- **Research Questions:**
 - Does receiving feedback from an LLM-simulated household on their energy plan improve the accuracy of participants' revised plans?
 - Is the effectiveness of LLM-generated feedback moderated by the initial information format in which the reduction goal was presented?
 - What aspects of the LLM's feedback (e.g., its specificity, the language used) are perceived as most helpful by participants?
 - Does interacting with an LLM simulating a real-world context enhance the perceived ecological validity of the planning task?

- **Connection to Sources:** This design incorporates the concept of LLM agents imitating human behavior and their potential for creating believable simulations. It also aligns with the vast body of research on feedback in energy conservation, with the LLM acting as a sophisticated feedback provider. The use of simulated households could address some ecological validity concerns.

4. LLM for Generating and Evaluating Planning Scenarios:

- **Study Design:** Utilize an LLM to create a wider and more diverse set of household scenarios, varying in demographics, climate, appliance ownership, and baseline energy consumption. Human participants would then perform the energy planning task for a subset of these LLM-generated scenarios, with the reduction goal presented in one of the three formats. Subsequently, a separate LLM could be trained to evaluate the accuracy and feasibility of the participants' plans for each scenario.
- **LLM Functionality:** The scenario-generating LLM would need to be prompted to create realistic and coherent household descriptions. The evaluation LLM would need to be trained on principles of energy consumption and savings to assess the plausibility of the proposed plans.
- **Research Questions:**
 - Does the effect of information format on planning accuracy generalize across a wider range of household scenarios generated by an LLM?
 - Can an LLM be effectively used to automate the evaluation of energy conservation plans, providing a more scalable approach to research in this area?
 - Are there specific types of scenarios (e.g., those with more complex appliance configurations) where certain information formats lead to greater accuracy, as identified by the LLM evaluation?
 - How does the consistency and reliability of LLM-generated scenario evaluations compare to human expert evaluations?
- **Connection to Sources:** This approach leverages the LLM's ability to generate diverse textual data to enhance the scope and generalizability of the study. The use of an LLM for evaluation aligns with research exploring LLMs as evaluators in educational contexts.

5. Combining Quantitative Planning with Qualitative Explanations Analyzed by LLMs:

- **Study Design:** Replicate the original study, but after completing the planning task, ask participants to explain their reasoning and the strategies they used to achieve the reduction goal in an open-ended text box. These qualitative responses would then be analyzed using an LLM.
- **LLM Functionality:** The LLM could be used to identify common themes, strategies, and difficulties expressed by participants in each information format condition. It could also assess the coherence and understanding reflected in their explanations.
- **Research Questions:**
 - Do the qualitative explanations provided by participants reveal different cognitive processes or challenges associated with planning in kWh, percentage, or USD?
 - Can an LLM identify a correlation between the strategies described by participants and their planning accuracy in each condition?
 - Are there systematic differences in the language used by participants in each condition when explaining their planning process?
 - Do participants in the kWh condition provide more concrete or appliance-specific explanations compared to those in percentage or USD conditions?
- **Connection to Sources:** This study utilizes the LLM's natural language processing capabilities for qualitative data analysis, offering deeper insights into the "why" behind the quantitative results. This approach is similar to using narratives to understand preferences and complements the quantitative measures of planning accuracy.

By integrating LLMs into studies investigating the impact of information format on energy planning, researchers can gain a more nuanced understanding of the cognitive processes involved, explore personalized interventions, and potentially enhance the scalability and ecological validity of their findings. These follow-up studies can contribute significantly to the development of more effective strategies for communicating energy information and promoting residential energy conservation.

Here are some ideas for a cognitive psychology study involving humans, AI, and decision-making in the context of energy use, connecting them to existing theoretical issues in cognitive science:

I. Energy Plan Creation & AI Assistance

- **Idea 1: Collaborative Energy Planning**
 - **Design:** Participants are tasked with creating an energy reduction plan for a hypothetical household. They are randomly assigned to one of three conditions:
 - * **Control:** Participants plan alone.
 - * **AI Assistant (Good):** Participants collaborate with an AI assistant that consistently generates high-quality, feasible energy-saving suggestions.
 - * **AI Assistant (Poor):** Participants collaborate with an AI assistant that generates inconsistent, sometimes impractical suggestions.
 - **Measures:**
 - * Quality of energy plans (e.g., feasibility, potential savings, comprehensiveness).
 - * User satisfaction with the AI assistant.
 - * Cognitive load experienced during planning (e.g., self-reported ratings, physiological measures).
 - **Theoretical Connection:** This study explores the impact of AI assistance on human decision-making, specifically in the context of complex, multi-faceted tasks like energy planning. It touches on concepts like **cognitive offloading**, where humans rely on external tools to reduce cognitive burden, and **human-AI collaboration**, examining how effectively humans and AI can work together to achieve a common goal.

- **Idea 2: Trust and Reliance on AI Energy Advisors**

- **Design:** Participants are presented with energy-saving recommendations generated by an AI advisor. The AI's performance is manipulated (e.g., consistently accurate, sometimes inaccurate, always provides justifications for recommendations). Participants choose between following the AI's advice or creating their own plan.
- **Measures:**
 - * Acceptance rate of AI recommendations.
 - * Perceived trustworthiness and competence of the AI advisor.
 - * Quality of participant-generated plans (when they choose not to follow the AI).
- **Theoretical Connection:** This study investigates the factors influencing **trust in AI systems**, particularly in domains with personal and financial implications like energy use. It also explores the potential for **over-reliance** on AI, and the conditions under which humans might critically evaluate AI-generated advice.

II. Representations of Energy Use

- Idea 3: Dimensions of Energy Consumption

- **Design:** Participants are presented with various representations of energy consumption data (e.g., numerical tables, graphs, visualizations). They are asked to identify the key dimensions of energy use (e.g., appliance type, time of day, season) and assign weights to their importance.
- **Measures:**
 - * Accuracy and completeness of identified dimensions.
 - * Assigned weights to different dimensions.
 - * Subjective ratings of the clarity and usefulness of different representations.
- **Theoretical Connection:** This study examines how humans **conceptualize and represent complex information** like energy consumption. It explores the role of **mental models** and **data visualization** in shaping understanding and decision-making.

- Idea 4: Abstraction Levels in Energy Planning

- **Design:** Participants are asked to create energy plans at different levels of abstraction:
 - * **Concrete:** Specifying kWh usage for each appliance.
 - * **Abstract:** Setting target average temperatures and appliance usage hours.
- **Measures:**
 - * Time taken to complete the plan at each level.
 - * Perceived difficulty and confidence in the plans.
 - * Quality of the plans (e.g., feasibility, potential savings).
- **Theoretical Connection:** This study investigates the cognitive processes involved in **hierarchical reasoning** and **problem-solving**. It explores how humans navigate between different levels of abstraction when making complex decisions, and the trade-offs involved in each approach.

III. AI Feedback and Decision-Making

- Idea 5: AI Feedback on Energy Plans

- **Design:** Participants create energy plans. They are then randomly assigned to receive feedback from an AI assistant:
 - * **Positive Feedback:** The AI praises the plan's strengths and offers minor suggestions for improvement.
 - * **Negative Feedback:** The AI highlights weaknesses in the plan and suggests significant revisions.
 - * **No Feedback:** Participants receive no feedback on their plan.
- **Measures:**
 - * Revisions made to the energy plan after receiving feedback.
 - * Subjective ratings of the helpfulness and persuasiveness of the feedback.
 - * Confidence in the final energy plan.
- **Theoretical Connection:** This study examines the impact of **feedback type** on human learning and decision-making. It explores how people process and integrate information from AI systems, and the factors that influence their acceptance of AI-generated feedback.