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Consumers underestimate the emissions associated with food but are aided by labels

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Food production is a major cause of energy use and GHG emissions, and therefore diet change is an important behavioural strategy for reducing associated environmental impacts. However, a severe obstacle to diet change may be consumers' underestimation of the environmental impacts of different types of food. Here we show that energy consumption and GHG emission estimates are significantly underestimated for foods, suggesting a possible blind spot suitable for intervention. In a second study, we find that providing consumers with information regarding the GHG emissions associated with the life cycle of food, presented in terms of a familiar reference unit (light-bulb minutes), shifts their actual purchase choices away from higher-emission options. Thus, although consumers' poor understanding of the food system is a barrier to reducing energy use and GHG emissions, it also represents a promising area for simple interventions such as a well-designed carbon label.

There is a widespread scientific consensus regarding the urgency to reduce GHG emissions[1], and on the need to study alternative interventions to do so. Much research has emphasized technological solutions such as greater energy efficiency and increased use of renewable sources of energy[2]. More recently, it has been recognized that diet change is also a potential solution worth exploring[3–5]. Economic analysis has examined the virtues of market-based mechanisms to influence demand, such as a carbon tax that increases prices in line with social costs[6]. Increasingly, however, social scientists have turned their attention to possible behavioural interventions to influence demand[7]. For example, social psychological research on social norms shows their effectiveness in producing behaviour change in some contexts[8,9]. However, social norms are problematic when the desired behaviour is rare[10]. Another intervention approach is to 'boost' consumer decision-making by providing relevant skills, knowledge and decision tools[11]. The efficacy of such boosts requires first understanding the relevant knowledge gaps.

Attempts to modify behaviour typically presume that consumers recognize the connection between their acts and the consequences for energy consumption and GHG emissions[12,13]. However, there is a growing body of research demonstrating that consumers are often unaware or misinformed. For example, Attari, et al.[14] found that people had a rudimentary understanding of the relative energy use of different electrical household appliances (henceforth, appliances) and activities. On average, people correctly recognized that refrigerators used more electricity than light bulbs, but were insensitive to the true difference between relatively high- and low-emitting appliances.

Research suggests that the food system contributes 19%–29% of global GHG emissions[15], which is similar to emissions from US household electricity use[16]. Many factors combine to produce such considerable emissions. Agriculture is highly industrialized. Refrigeration and transportation tend to depend heavily on fossil fuels. Natural gas is a key input in the manufacture of fertilizer. Cattle raised for beef and dairy products are major sources of methane. Moreover, the process of raising meat is inherently inefficient: fertilizer is used to grow feedstock, but only a small portion of the feed becomes animal protein; the rest becomes manure and methane. Thus, it takes 38 kg of plant-based protein inputs to produce 1 kg of edible beef[17]. Finally, in many parts of the world, burning forests to create grazing and agricultural land also emits GHG emissions. A significant reduction in GHG emissions from food could be achieved by changing consumers' diet; in particular, by moving toward more vegetarian or vegan meals[18,19]. Even changing the type of meat consumed could have a large beneficial environmental impact[20].

Existing research, which typically asks consumers via survey to indicate knowledge or agreement with facts about the environmental impact of food, suggests that consumer awareness of the environmental impact of meat production is low[21–24]. Importantly, however, those who believe that reducing meat consumption effectively reduces GHG emissions are much more likely to intend to reduce eating meat[22,25].

Understanding consumers' perceptions of energy consumption and GHG emissions of individual food items in a way similar to Attari et al.[14] is important because it can inform the design of information interventions to help consumers understand the true impact of their behaviours. Experimental studies investigating simple interventions to increase pro-environmental food consumption behaviour have yielded only modest results[26]. Therefore, additional research that identifies effective 'boosts' is needed.

One of the most straightforward ways to attempt to influence food choice is through labels[27]. For example, a carbon label communicates information about the total amount of GHG emissions from within a defined supply chain (for example, from cradle to grave). Carbon labels provide information to consumers that can be factored into purchase choices and also exert pressure on manufacturers and retailers to provide consumers with lower-emission options[28].

The research associated with environmental labels on foods is mixed. Some research suggests that consumers desire carbon labels[29,30]. However, other research suggests that consumers barely use environmental labels when making food choices[31]. Still other research indicates that environmental labels can move consumption

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towards foods with lower GHG emissions under certain conditions[26]. Several countries, including the UK, USA and Australia, have developed carbon labels that have been adopted for some products[32]. Labels vary from simply stating the manufacturer's commitment to reduce GHG emissions to stating a numerical estimate of the carbon dioxide equivalent emitted to providing a green–yellow–red traffic light system indicating levels of GHG emissions[33]. However, many consumers find it difficult to understand existing carbon labels[29,30]. This confusion is problematic because labels are effective in changing consumers' purchase decisions only when they provide information that is easy to understand. Confusion may be responsible for the lack of effectiveness.

In Study 1 (modelled after ref. [14], see also ref. [34]), we elicited people's perceptions of the energy consumption (Study 1A) and GHG emissions (Study 1B) embedded in food production and transportation. We examined both energy consumed and GHG emissions because they are not perfectly correlated and different audiences may have interests in just one of these areas. To serve as a reference, we also measured the same perceptions for common appliances, thus extending the work of Attari et al.[14] to include additional items and GHG emissions. We found systematic underestimation for both food and appliances with food impacts being underestimated significantly more than those of appliances. In Study 2, we found that the provision of food GHG emissions information in terms of a familiar metric influenced food choice behaviour, such that consumers' choices shifted toward foods with lower GHG emissions when such information was made explicit.

Perceived versus actual energy use and GHG emissions

Participants estimated the energy consumption (Study 1A, $n=518$) or GHG emissions (Study 1B, $n=514$) from producing and transporting a serving of 19 foods and from the 1 h use of 18 appliances (8 of which were the same as those in ref. [14]; see Methods and Supplementary Note 1). The items were selected to span a wide range of energy consumption. The correlation between the actual values of energy use and GHG emissions was 0.96 for foods ($P<0.0001$) and 1.00 for appliances. Note that in the food domain, GHG emissions result not only from energy use in food production but also from other sources (for example, methane release). In both studies, participants were provided with reference information for a 100-W incandescent bulb used for 1 h (that is, it consumed '100 units' of energy or it emitted '100 units' of GHG emissions). Two additional studies that included a food reference unit—a medium-sized tomato—yielded parallel results (see Supplementary Note 2).

Figures 1 and 2 show participants' estimated energy use and GHG emissions plotted against actual values after transforming both variables with base-10 logarithms to reduce positive skew. Actual values were calculated from literature-based best estimates obtained by averaging the values reported in multiple sources (see Supplementary Note 3 and Supplementary Tables 2–4). For each dataset, we ran two mixed-effects models using the maximum-likelihood method (see Table 1). We used the mixed-effects model because it enabled the modeling of correlated data—inherent to the nature of our design—without the violation of important regression assumptions[35]. The first model in each study regressed estimated values on actual values to obtain an intercept, slope and main effect for domain. Participant 'ID' was entered as a random effect. We entered 'domain' (coded $0=$appliances, $1=$foods), the log of the actual value (mean centred; 'actual') and the quadratic 'actual^2' as independent variables. We entered the log of the estimated value (centred relative to the mean of actual) as the dependent variable. As in Attari et al.[14], the intercept and slope of actual was modelled as a random effect and thus free to vary. The second model in each study added interaction terms between domain and actual, and between domain and actual^2. We report results from additional models that include a range of covariates and that assume minimum plausible actual values in Supplementary Note 4. These confirm the results presented in Table 1 and described below.

For perfectly accurate estimates, the lines of best fit plotted in Figs. 1 and 2 would lay along the identity line with an intercept of 0 and a slope of 1. However, the results in Table 1 show that, for both studies, the average intercept (which gives the average elevation of estimate at the mean of actual when domain$=0$) was significantly negative. This indicates that participants underestimated energy consumed and GHG emissions for appliances. In both studies, there was a significant main effect of domain. As expected, this negative coefficient indicates that estimates were significantly lower for foods than for appliances. In both studies, there was also a significant effect of actual, indicating that people gave higher estimates for items with higher actual values. As expected, however, these slopes were significantly less than 1 (the 95% confidence intervals ranged between 0.14 and 0.24), showing that people were insufficiently sensitive to the magnitude of difference between items. Finally, in both studies there was also a significant effect of actual^2, reflecting that moderate-energy-consuming/GHG-emitting items were estimated relatively more inaccurately than low- or high-energy consuming/GHG-emitting items, thus producing a quadratic 'U' shape.

We also tested for interactions between domain and actual and between domain and actual^2, which were both significant. In both studies, the positive relation between actual and estimated values was stronger for appliances than for foods, and the U quadratic shape was more pronounced for foods than for appliances. Put simply, consumers were relatively insensitive to the difference in energy consumed and GHG emissions of most foods (for example, fruits, vegetables, nuts, milk and cheese), but were relatively more sensitive to the difference in energy consumed and GHG emissions between red meat (for example, beef) and non-meat items (for example, potatoes). Nevertheless, they underestimated red meat by the widest margin.

The effectiveness of a carbon label

Study 1 suggests that consumers significantly underestimate the energy consumption and GHG emissions associated with food production and transportation, and to a greater degree than for appliances. The substantial underestimation of the environmental impact of the food's life cycle is likely to be reflected in consumers' food choices. Namely, consumers may be unwilling to move away from high-GHG-emitting foods such as beef because of a lack of understanding of beef's environmental consequences. In Study 2, we tested whether correcting these misperceptions with a carbon label may be a viable strategy to influence behaviour.

Lessons from nutrition and fuel economy labelling suggest that an effective carbon label should be simple to understand and include reference values that permit comparisons and put information in context[36,37]. One effective approach used with fuel economy labels has been to translate obscure attributes into more comprehensible attributes[38,39]. We therefore designed a label that provides salient, concrete GHG information and that facilitates the understanding of information by expressing GHG emissions in terms of a familiar unit (equivalent light-bulb minutes), and facilitating evaluation by using a simple green-to-red scale relative to products in the same category[40].

Participants ($n=120$) were presented with a menu on a computer screen of six cans of soups—three beef and three vegetable—and were asked to buy three cans of soup using some of the money they received for showing up to participate (see Methods and Supplementary Note 5). For those in the control group, each soup was described in terms of name, image, serving size, price, calories and information about the macronutrients. The label group was additionally presented with GHG emission information in

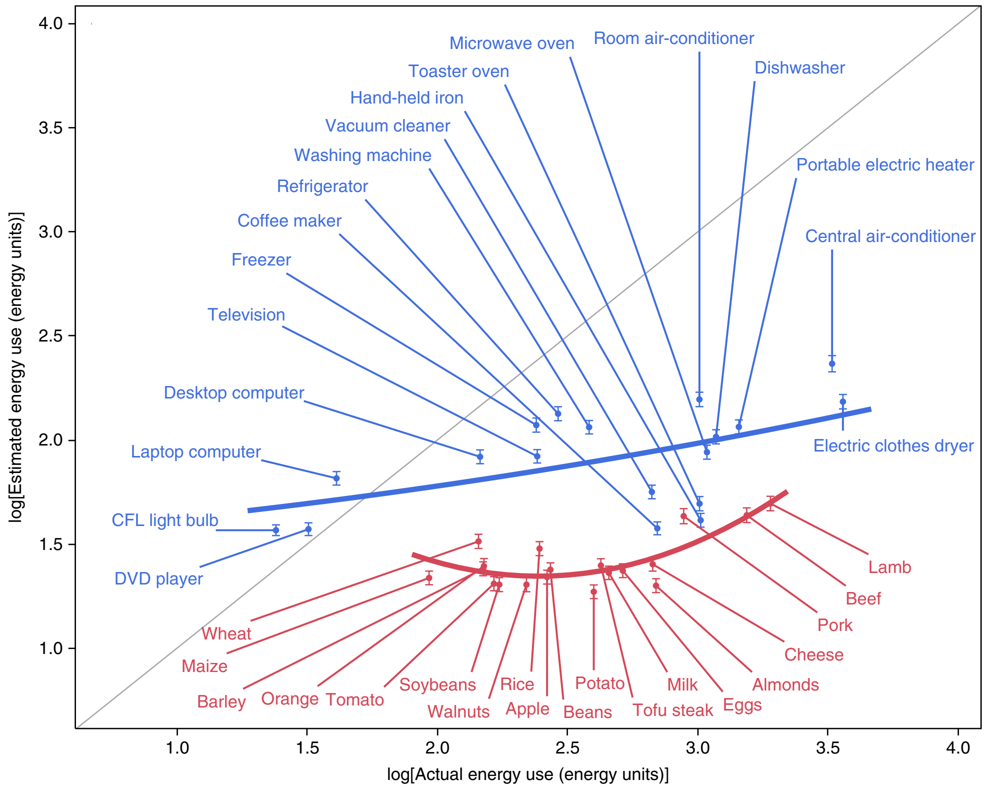

Fig. 1 | Mean estimates of energy used relative to actual energy used. The red fitted line depicts the relationship between the actual energy consumed throughout the life cycle of 19 foods (*x* axis) and the estimates provided by Study 1A participants (*y* axis). The blue fitted line depicts the relationship between the actual energy used of 18 electrical appliances (*x* axis) and the estimates provided by Study 1A participants (*y* axis). Accurate estimates would produce a set of points that fall along the grey 45° line. As shown, participants ($n = 518$) underestimated the energy consumption of all foods and almost all appliances (with the exception of compact fluorescent lamp (CFL) light bulbs, laptop computers and DVD players). The underestimation was greater for foods than for appliances. Note that all estimates are expressed in terms of energy units and participants were told that a 100 W incandescent light bulb turned on for 1 h uses 100 energy units. All data are logged. The error bars represent the standard error of the mean.

terms of lb CO_2e, 'light-bulb minutes' and a coloured rating scale ranging from 'Lower Carbon Footprint' (in a green zone) to 'Higher Carbon Footprint' (in a red zone) based on the range of actual values observed for soups (see Fig. 3 for an example). The main dependent variable was the number of beef soups purchased.

The carbon label had the predicted effect: those in the label group ($M = 0.98$, s.d. $= 1.04$) purchased fewer cans of beef soup than those in the control group ($M = 1.51$, s.d. $= 1.06$), $t(118) = -2.74$, $P = .007$, $d = 0.50$ (all significance tests are two-tailed; see Supplementary Note 6 for regressions including a range of covariates).

To examine the impact of the label on participants' knowledge, we calculated the ratio between estimated beef soup GHG units to estimated vegetable soup GHG units. We removed from the analysis two outliers who were more than six standard deviations from the mean ratio ($M = 3.67$, s.d. $= 7.07$, before exclusion). The true ratio was approximately 10 (see Supplementary Note 7). A two-sided *t*-test revealed that those in the label group ($M = 3.45$, s.d. $= 2.65$) estimated a higher ratio of emissions from beef over vegetables than those in the control group ($M = 2.16$, s.d. $= 1.23$), $t(116) = 3.38$, $P = .001$, $d = 0.62$.

To examine whether the label affected soup purchases because of a change in knowledge, we conducted a mediation analysis using Hayes' PROCESS tool for SPSS[41]. In the mediation analysis (Model 4, 5,000 bootstrap samples), the independent variable was 'label' (0 = absent, 1 = present), the mediating variable was the estimated beef-to-vegetables ratio and the dependent variable was the number of beef soups purchased. As shown in Fig. 3, the analysis revealed the expected significant indirect effect of label on the number of beef soups purchased via the estimated beef-to-vegetables ratio, $B = -0.11$ (95% confidence interval $= -0.25, -0.01$).

These results suggest that provision of food GHG emissions information in an understandable way increases consumers' tendency to choose relatively low-emission options compared to when no GHG emission information is provided. On average, this information improved understanding of relative GHG emissions between alternatives, which in turn shifted choice towards lower-GHG-emitting options.

Discussion

People tend to underestimate the energy consumed by and GHG emissions from the production, storage and transport of a range of foods. This blind spot regarding food production as a source of energy consumption and GHG emissions may have consequences for related daily decisions.

In general, people tended to appropriately rank items by energy used and GHG emissions. For example, higher GHG emissions were estimated for producing a serving of beef than producing an apple. However, the actual difference in magnitude between high- and low-emission items was not reflected in people's estimates. For example, items associated with high emissions, such as beef, were underestimated much more than items associated with low emissions, such as apples. The worrying implication of this finding is that the typical consumer is unaware of the benefits that can be obtained by shifting away from high-energy and high-GHG-emission options. For example, according to one estimate for the average weekly diet of an Australian family, replacing ruminant meat (for

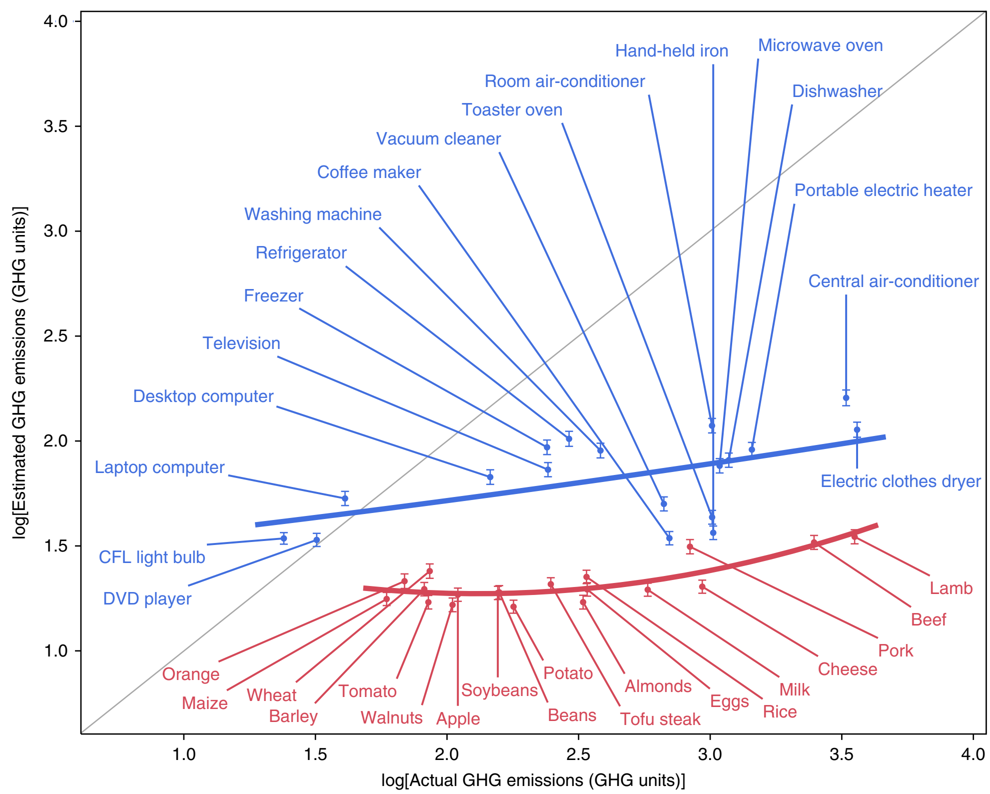

Fig. 2 | Mean estimates of GHG emitted relative to actual GHG emitted. The red fitted line depicts the relationship between the actual GHG emitted throughout the life cycle of 19 foods (*x* axis) and the estimates provided by Study 1B participants (*y* axis). The blue fitted line depicts the relationship between the actual GHG emitted of 18 electrical appliances (*x* axis) and the estimates provided by Study 1B participants (*y* axis). Accurate estimates would produce a set of points that fall along the grey 45° line. As shown, participants ($n = 514$) underestimated the GHG emitted of all foods and almost all appliances (with the exception of CFL light bulbs, laptop computers and DVD players). The underestimation was greater for foods than for appliances. Note that all estimates are expressed in terms of GHG units and participants were told that a 100-W incandescent light bulb turned on for 1 h emits 100 GHG units. All data are logged. The error bars represent the standard error of the mean.

Table 1 | Results of multilevel regressions for predicting consumers' perceptions of energy consumption (Study 1A) and GHG emissions (Study 1B)

	Study 1A		Study 1B	
	Model 1	**Model 2**	**Model 3**	**Model 4**
Intercept	−0.709***	−0.693***	−0.723***	−0.713***
Domain (domain)	−0.464***	−0.530***	−0.466***	−0.509***
Log of actual value (actual)	0.217***	0.210***	0.161***	0.176***
Quadratic term (actual²)	0.065***	0.025*	0.039***	0.010
domain × actual		−0.033*		−0.062***
domain × actual²		0.421***		0.132***

The independent variable domain refers to whether participants were estimating foods (coded '1') or appliances (coded '0'). The independent variable actual, which was logged and mean-centred, refers to the actual energy consumed or GHG emissions for each item. The dependent variable—estimated, which was also logged and centred relative to the mean of actual—refers to the participant's estimated energy consumed or GHG emissions for each item. Coefficients are unstandardized. ***$P < 0.001$, *$P < 0.05$.

example, beef) with non-ruminant meat (for example, duck), and selecting alternative fish species, produces an estimated 30% reduction in food-related emissions[3].

A key question that emerges from our observations is: why do consumers underestimate energy consumed and GHG emissions? Previous research in cognitive psychology shows that people often overestimate their understanding of common everyday objects and activities, such as how a zipper operates[42–44]. Rozenblit and Keil[43] argue that the folk theories people hold are fragmentary and incomplete but largely unchallenged—people rarely need to explain the operation of complex everyday objects and therefore are unaware of the gaps in their understanding. We believe that food is a similarly familiar but complex phenomenon. Just as with zippers, consumers encounter food every day; however, the complex production and distribution process is hidden. For example, many consumers may be unaware that cattle release methane, a GHG that is 28–36 times more potent than CO_2[45]. Therefore, we suggest that one of the main reasons for misperception is that consumers fail to consider important factors underlying energy consumption and GHG emissions, and this failure is accentuated for food items. Unlike appliances, which have energy labels, are plugged into an electrical outlet, emit heat, have clear indications of drawing power, and their usage affects a monthly electricity bill, the consumption of energy in the production and transportation of food is largely invisible[46]. Moreover, unlike energy, which is closely associated with the burning of fossil fuel and release of carbon dioxide, the GHG emissions embodied in food result from different processes of the life cycle, such as the large amounts of nitrous oxide emissions from fertilizer[47]. This may explain why we found greater underestimation for food than for appliances. Recent support for this general explanation comes from Attari et al.[48], who asked people to draw diagrams illustrating how water reaches the tap in an average home in the United States. The results revealed major gaps in understanding.

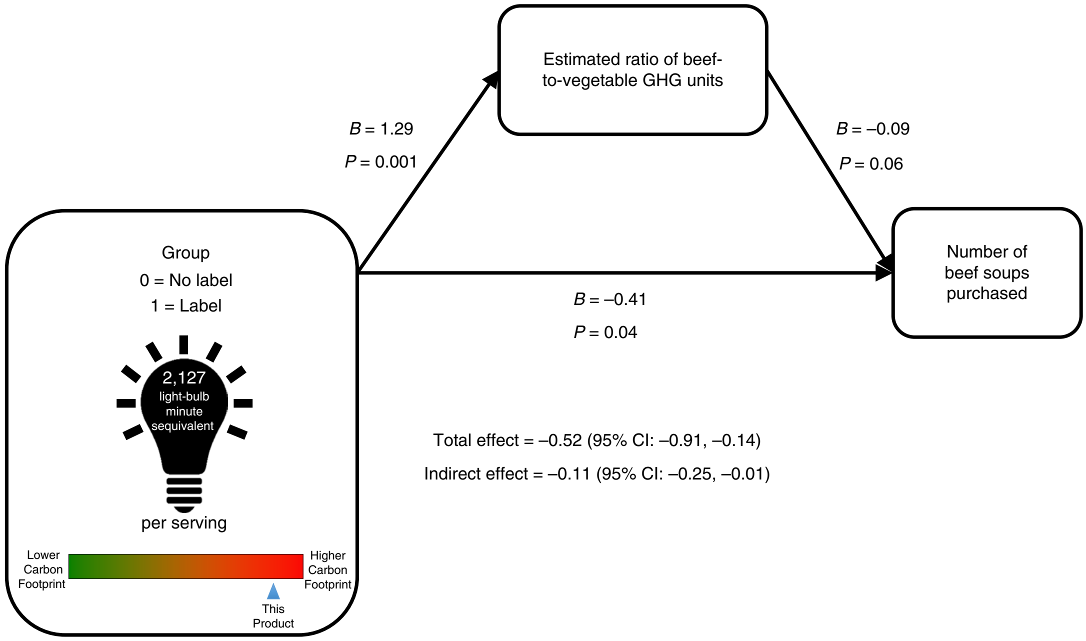

Fig. 3 | Results of a mediation analysis in Study 2. Participants were either presented with information about the GHG emissions embodied in the soup options or were not. For the former group, information was presented in terms of equivalent light-bulb minutes as well as a green-to-red scale indicating the GHG emissions of the current product relative to others in the same category. An example is provided for Vegetable Beef Soup in the study. The mediation analysis revealed an indirect effect of GHG emissions information on the number of beef soups purchased via the estimated ratio of beef-to-vegetable GHG units. CI, confidence interval.

A second key question that emerges from our observations is how to help consumers improve their general ability to make more accurate estimates. In Study 2, we found that provision of GHG emission information in a relatable format led consumers to more frequently purchase relatively low-emission foods. It may be that a carbon label serves as a decision signpost: reminding consumers of their values and then directing them to options most consistent with those values[39]. We also acknowledge that knowledge alone is often insufficient to change behaviour[49]. In the real marketplace, factors such as perceived behavioural costs[50], norms[51] and identity[52] also influence behaviour. Moreover, the extent to which knowledge influences behaviour in this context is influenced by factors such as political affiliation and level of trust in scientists[53]. Therefore, our promising observations warrant replication outside a laboratory setting.

A limitation of our research is the data we used as best estimates of the 'true' values of energy use and GHG emissions associated with food and appliances[3]. Different environmental life-cycle analyses produce different results depending on geographic, temporal or system boundaries, and other assumptions, and hence the true value is not a point estimate but a range. Fortunately, there does seem to be convergence in the general ranking of energy use and GHG emissions associated with broad food categories[3,54], and our conclusions are unlikely to change due to this factor alone. Furthermore, a sensitivity analysis indicated that participants' estimates were lower than even the minimum value reported across different sources. The difficulty in quantifying with precision the environmental impacts of foods and the variability of these impacts across supply chains suggests that a label reporting a range of GHG emissions representing both variability and uncertainty of these estimates may be a more suitable approach than a food label with a specific carbon score. This range could be implemented as a band that covered the space between the lower and upper bound (for example, 10th and 90th percentiles) of the distribution of possible GHG emissions for a given food. A traffic light code could still compare the extremes of this range with the least and most environmentally friendly foods. Uncertainty bounds are usually reported as part of life-cycle assessment studies, but more research should be conducted on how to best communicate this to consumers.

Online content

Any methods, additional references, Nature Research reporting summaries, source data, statements of data availability and associated accession codes are available at https://doi.org/10.1038/s41558-018-0354-z.

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Author contributions

A.R.C., R.P.L., S.H. and D.P.-E. designed the research. A.R.C. and S.H. performed the research. A.R.C. and S.H. analysed the data. A.R.C., R.P.L. and D.P.-E. wrote the paper.

Competing interests

The authors declare no competing interests.

Additional information

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Methods

For all studies, the sample size was selected on the basis of similar past research. The actual energy and GHG emissions from the foods and appliances we used are presented in Supplementary Note 3 and Supplementary Tables 2–4. The research was approved by the Duke University IRB board and the RMIT University Ethics Committee. Informed consent was obtained from all participants.

Study 1A. *Participants.* The 518 participants who completed the study were recruited from the Qualtrics online panel and were paid for completion. The survey was available only to people in the United States. Quota sampling ensured that the sample reflected the American adult population in terms of age, gender and race. The participants ranged in age from 18 to 84 years with a mean of 43.6 (s.d. = 14.6). Among the survey respondents, 52% were female and 59% were employed full time or part time. Racially, 63% were non-Hispanic White, 16% Hispanic, 12% African American, 5% Asian, and 4% as other. Politically, 37% identified as Democrats, 31% as Independent, 28% as Republican, and 4% as other.

Materials and procedure. Participants were first asked to indicate the percentage of household GHG emissions produced from operations, transportation and food production (see Supplementary Note 1 for the full methods). Next, participants were asked to estimate how many units of energy are consumed in the production and transport of a serving size of 19 foods and the powering for 1 h of 18 appliances. The reference was that using a 100-watt incandescent light bulb for 1 h consumes 100 units of energy. Half of the participants judged the food domain items first and the others judged the appliance domain items first. Within each domain, the order of the items was randomized for each participant. Each domain of items also included an attention check item that read `Enter the number 100 in this box'. The participants who failed this attention check question were immediately filtered out of the survey. On the next page, participants answered two further attention check questions related to the task. On the next page, participants were asked to complete the revised New Ecological Paradigm revised (NEPr) scale, a 15-item questionnaire for assessing pro-environmental worldview[55]. Scores on the NEPr scale range from 15 to 75 with higher scores indicating a more pro-environmental worldview. Finally, participants answered a set of basic demographic questions. We also excluded one participant who completed the study in less than a third of the median soft-launch survey complete time.

Study 1B. *Participants.* The 514 participants who completed the study were recruited from the Qualtrics online panel and were paid for completion. The survey was available only to people in the United States. Quota sampling ensured that the sample reflected the American adult population in terms of age, gender and race. The participants ranged in age from 18 to 83 years with a mean of 43.5 (s.d. = 14.4). Among the survey respondents, 52% were female and 53% were employed full time or part time. Racially, 64% were non-Hispanic White, 15% Hispanic, 12% African American, 5% Asian, and 4% as other. Politically, 40% identified as Democrats, 31% as Independent, 23% as Republican, and 6% as other.

Materials and procedure. The materials and procedure were identical to Study 1A except that the reference was that using a 100-watt incandescent light bulb for 1 h released 100 units of GHG emissions (see Supplementary Note 1 for the full methods).

Study 2. *Participants.* The 120 participants who completed the study were recruited from the Duke University Behavioral Research community participant pool and were paid for completion. The convenience sample ranged in age from 18 to 74 years with a mean of 27.4 (s.d. = 9.5). Among the survey respondents, 62% were female and 61% were employed full time or part time. Racially, 33% were Caucasian/White, 8% Hispanic/Latino, 17% African American, 40% Asian/Pacific Islander, and 2% as other. Politically, 54% identified as Democrats, 28% as Independents, 4% as Republican and 14% as other.

Materials and procedure. The study was carried out in a computer laboratory together with two other, unrelated studies. The data were collected over multiple sessions in a single day. Each session comprised up to 16 participants. Research assistants, blind to the hypotheses, managed the data collection. Before beginning the bundle of studies, participants answered a series of demographic questions. When the current study began, participants were informed that they would earn US$6 for completing the study but that US$3 of the payment was to be spent purchasing goods that they would actually get at the end of the study. Next, participants were presented on screen with six cans of soup—three beef soups and three vegetarian soups—and asked to buy three of the soups (see Supplementary Note 5 for the full methods). Each type of soup could be purchased only once. The arrangement of the soups was the same for all participants. The information available for each soup was: name, image, price, serving size, calories, fats per serving, carbohydrates per serving and proteins per serving. Depending on the group allocation, participants were also presented with GHG emissions per serving (in terms of grams of carbon dioxide equivalent and light-bulb minutes equivalent), as well as a GHG emissions rating per serving. The rating displayed an arrow 'This Product' on a continuum ranging from Lower Carbon Footprint, coloured green, to Higher Carbon Footprint, coloured red. On the next page, participants were asked, as in Study 1B, to estimate how many units of GHG emissions were released in the production and transport of a serving size of beef soup and vegetable soup. Next, participants answered three attention check questions followed by a question measuring the participant's familiarity with the soups presented in the study. Next, participants completed the NEPr[55]. Next, participants completed a modified version of the Food Choice Questionnaire, which measures 36 factors that drive food choices such as health and convenience[56,57]. Finally, participants answered additional demographic questions including type of diet.

Data availability

The data that support the plots within this paper and other findings are available at https://osf.io/smj67.

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