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Public perceptions of how to reduce carbon footprints of consumer food choices

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Abstract

Carbon footprints—the greenhouse gas (GHG) emissions associated with consumer food choices—substantially contribute to climate change. Life cycle analyses from climate and environmental sciences have identified effective rules for reducing these food-related GHG emissions, including eating seasonal produce and replacing dairy and red meat with plant-based products. In a national UK survey, we studied how many and which rules our participants generated for reducing GHG emissions of produce, dairy, and protein-rich products. We also asked participants to estimate GHG emission reductions associated with pre-selected rules, expressed in either grams or percentages. We found that participants generated few and relatively less effective rules, including ambiguous ones like 'Buy local'. Furthermore, participants' numerical estimates of pre-selected rules were less accurate when they assessed GHG emission reductions in grams rather than in percentages. Findings suggest a need for communicating fewer rules in percentages, for informing consumers about reducing food-related GHG emissions.

1. Introduction

Food production and agriculture account for over 25% of annual anthropogenic global greenhouse gas (GHG) emissions (Springmann *et al* 2016). Due to a growing world population, global food-related GHG emissions are expected to increase substantially (Bajželj *et al* 2014, He *et al* 2018). Shifting towards more sustainable diets is considered essential for reducing food-related GHG emissions, alongside technological advances in the food system (Hedenus *et al* 2014). Collective dietary changes among consumers could potentially reduce 29%–70% of food-related GHG emissions, while also improving human health (Springmann *et al* 2016, Charles *et al* 2018). Life cycle analyses from climate and environmental sciences have quantified the GHG emissions or 'carbon footprints' associated with different food groups and their supply chains (Clune *et al* 2017; table S4 is available online at stacks.iop.org/ERL/14/114005/mmedia). For example, GHG emissions of produce can be reduced by eating fruits and vegetables such as raspberries, tomatoes and carrots, only when they are season (Röös and Karlsson 2013, Foster *et al* 2014). GHG emissions associated with protein-rich products can be reduced by replacing meat with plant-based products (Clune *et al* 2017). However, for non-expert consumers, understanding the various steps of food supply chains and how they influence food-related GHG emissions may be rather daunting (Camilleri *et al* 2019).

Behavioral decision researchers have found that teaching consumers a few simple 'rules of thumb' can potentially facilitate faster and more effective decisions, about for example health, management, and finance (Gigerenzer *et al* 1999, Gigerenzer and Gaissmaier 2011, Artinger *et al* 2015, Hafenbrädl *et al* 2016). Consumers already use simple rules when choosing what they would like to have for lunch (Schulte-Mecklenbeck *et al* 2013). To effectively communicate simple rules that consumers can use for reducing food-related GHG emissions, we first need a better understanding of how they (mis)perceive such rules (Bruine de Bruin and Bostrom 2013).

1.1. Perceptions of pre-selected rules for reducing food-related carbon footprints

Several studies have asked participants to assess how much GHG emissions can be reduced by implementing specific rules that were pre-selected and presented by researchers (Lea and Worsley 2008, Tobler *et al* 2011, Hartmann and Siegrist 2017, Shi *et al* 2018). Participants tended to overestimate how much GHG emissions can be reduced by 'Buying organic', 'Buying local', 'Avoiding excessive packaging' or 'Avoiding high-food miles products'. They tended to underestimate the effectiveness of 'Replacing red with white meat with plant-based products' (Lea and Worsley 2008, Tobler *et al* 2011, Hartmann and Siegrist 2017, Shi *et al* 2018). Consumers may also be unsure which rules to implement (Truelove and Parks 2012), lack pro-environmental attitudes, or have little knowledge about climate change (Tobler *et al* 2011).

However, when consumers seek to reduce the GHG emissions of their food choices, in for example a restaurant or a supermarket, they will likely have to generate their own rules. In other contexts, it has been suggested that especially less informed consumers may end up generating rules that are less effective than the rules experts would recommend (Bridgeman and Morgan 1996, Bruine de Bruin and Fischhoff 2000). Studies that have asked participants to generate rules for reducing their overall carbon footprints (using the so-called 'cue generation paradigm'; Ruggeri and Katsikopoulos 2013, Ruggeri *et al* 2015) revealed a focus on relatively less effective rules such as 'Turn off the lights' and ambiguous ones such as 'Green consumption' (Read *et al* 1994, Attari *et al* 2010, Reynolds *et al* 2010). Studies have yet to examine which rules consumers generate for reducing food-related carbon footprints.

1.2. Formats for communicating food-related carbon footprints

Effectively communicating simple rules about how to reduce food-related carbon footprints requires the use of numerical formats that consumers can understand (Hoffrage *et al* 2000, Yang *et al* 2012, Bruine de Bruin and Bostrom 2013). People may perceive changes in numerical health risks more accurately, when health communications present simple frequencies rather than percentages (Gigerenzer *et al* 2010). Similarly, drivers may make more accurate estimates of the speed required to arrive at a destination on time when speed is expressed in 'minutes per kilometer' instead of 'kilometers per hour' (Eriksson *et al* 2015). Drivers' estimates of fuel use are more accurate when fuel use is described in 'gallons per mile' instead of 'miles per gallon' (Larrick and Soll 2008). Additionally, the question arises whether participants may estimate reductions in food-related carbon footprints more accurately, when those are expressed in grams of GHG emissions or in percentages—the two numerical formats most commonly used in life cycle analyses from climate and environmental sciences (e.g., Hedenus *et al* 2014, Foster *et al* 2014, Lee *et al* 2015, Aguilera *et al* 2015a, 2015b, Clune *et al* 2017; table S4).

1.3. Research questions

In the present study, we recruited a UK national sample to examine perceptions of rules for identifying foods with a low carbon footprint. They completed two tasks. In the first task, participants were asked to generate their own rules (using the so-called 'cue generation paradigm'; Ruggeri and Katsikopoulos 2013, Ruggeri *et al* 2015), for reducing the carbon footprints of one of three food groups, including produce (such as tomatoes and carrots) dairy (such as cheese or milk), or protein-rich products (such as beef or tofu; see table S1). Participants were also asked how effective they perceived each of their generated rules to be. In the second task, participants estimated the reductions in GHG emissions associated with four pre-selected rules, in either grams or in percentages. Based on these two tasks, we examined the following research questions:

(a) How many rules did participants generate for identifying produce, dairy, or protein-rich products with a low carbon footprint?

(b) What percent of participants generated the most effective rules for identifying produce, dairy, or protein-rich products with a low carbon footprint (as identified in existing life cycle analyses from climate and environmental sciences)?

(c) How accurate were participants when estimating reductions in GHG emissions for pre-selected rules, in grams versus percentages (as compared to life cycle analyses from climate and environmental sciences)?

For each research question, we also examined the role of participants' environmental worldviews (Dunlap *et al* 2000), climate change knowledge (Shi *et al* 2015), numeracy (Cokely *et al* 2012), and 'need for cognition' or motivation to solve complex problems (Cacioppo *et al* 1984). Each of these individual-difference variables has been deemed relevant to facilitate the understanding of communications about risks and climate change (Attari et al 2010, Duckworth et al 2011, Cokely et al 2012, Bruine de Bruin and Bostrom 2013).

2. Methods

2.1. Participants

UK participants were recruited online in January 2018, by the marketing company ResearchNow. They received £3.30 upon completion of our online survey, which was approved by the ethical review board of the University of Leeds. Of the 6100 individuals who were initially contacted, 733 (12%) opened the link to our survey. Of those, 627 (86%) completed it. Table S3 in the supplemental material (available online at stacks.iop.org/ERL/14/114005/mmedia) provides participants' demographic characteristics, while also comparing those who completed the survey to the UK's population. Participants' ages ranged from 18 to 80 years, with a mean of $M = 43$ (Mdn = 40, SD = 15), which is similar to the UK population (Mdn = 40). Overall, 41% of our participants were male, which is slightly lower than the percent of males in the UK population (49%). Of our participants, 57% had at least a college degree; compared to 27% in the UK population. These demographic characteristics were included as control variables in our linear regression analyses.

2.2. Study design

Participants first completed a task in which they generated rules for reducing food-related carbon footprints (following the 'cue-generation paradigm' from behavioral decision sciences; Ruggeri and Katsikopoulos 2013, Ruggeri et al 2015). They also indicated how effective they perceived their generated rules to be. They then completed a second task in which they numerically estimated reductions of GHG emissions associated with rules that were pre-selected by the authors. Participants were randomly assigned to complete these two tasks for one of three food groups, including produce ($N = 210$), dairy ($N = 208$), or protein-rich products ($N = 209$). In the second task, participants were also randomly assigned to making their numerical estimates for reductions in GHG emissions in grams ($N = 308$) or in percentages ($N = 319$).

2.2.1. Generated rules

In the first task, we asked participants to generate rules using the question 'What characteristics do you think are typical for [produce/dairy/protein-rich products] with a low carbon footprint? Please list as many characteristics as you can think of.' To facilitate the generation of rules, participants received a list of the most frequently sold food items in UK supermarkets for their assigned food group (produce, dairy, or protein-rich; see table S1 in the supplementary materials). Participants then rated how effective (or 'informative') they perceived each of their generated rules to be for reducing food-related GHG emissions, on a 1–7 scale.

2.2.2. Pre-selected rules

In the second task, participants estimated how much GHG emissions could be reduced by implementing four pre-selected rules for their assigned food group (produce, dairy, or protein-rich products), following procedures from previous research (Attari et al 2010, Camilleri et al 2019). Participants who were assigned to evaluating pre-selected rules in grams were asked 'How many grams of GHGs such as CO2 do you think are SAVED by the following changes?' Participants who were assigned to make these estimates in percentages received the same question, except that 'grams' was changed to 'percent'. All participants were subsequently presented with the four pre-selected rules for their assigned food group. In order of most to least GHG emission reductions, the pre-selected rules for produce included: (1) 'Growing 1 kg of produce on a field outside instead of in a heated greenhouse'; (2) 'Producing 1 kg of produce organically instead of conventionally'; (3) 'Producing 1 kg of produce locally rather than importing it from another European country' and (4) 'Packing 1 kg of produce into a paper bag instead of into a plastic shell'. For dairy, the pre-selected rules included (1) 'Producing 1 kg of plant-based margarine instead of 1 kg of butter'; (2) 'Producing 1 l of soy milk instead of 1 l of conventional milk'; (3) 'Producing 1 l of organic milk instead of 1 l of conventional milk' and (4) 'Producing 1 l of milk locally (within the same county, i.e. approximately a 50 miles radius) instead of importing it from a different region of the UK (400 miles radius)'. For protein-rich products, the pre-selected rules included (1) 'Producing 1 kg of fresh fish instead of 1 kg of fresh beef'; (2) 'Producing 1 kg of chicken instead of 1 kg of pork'; (3) 'Producing 1 kg of organic meat instead of 1 kg of conventional meat'; and (4) 'Producing 1 kg of meat in the UK instead of importing it from a European country'.

Participants also rated how confident they were about each of their four estimates, on a 1–7 scale. Confidence ratings were relatively consistent across participants' four ratings, independent of whether they assessed numerical estimates in grams versus percentages, for produce (Cronbach's $\alpha = 0.97$ versus $\alpha = 0.92$), dairy (Cronbach's $\alpha = 0.98$ versus $\alpha = 0.96$), or protein-rich products (Cronbach's $\alpha = 0.96$ versus $\alpha = 0.96$). For each participant, we therefore averaged their four confidence ratings.

2.2.3. Individual-difference variables

Participants' environmental worldviews were assessed on the 15-item New Ecological Paradigm scale, with an example question asking 'When humans interfere with nature it often produces disastrous consequences' (Dunlap et al 2000). Climate change knowledge was assessed through true/false/do not know statements about the mechanisms and consequences of climate change, including 'Burning oil, among other things, produces CO_2' (Shi *et al* 2015). Numeracy was assessed through the Berlin Numeracy Test, including questions like 'Imagine we are throwing a five-sided die 50 times. On average, out of these 50 throws how many times would this five-sided die show an odd number (1, 3 or 5)?—out of 50 throws.' Following adaptive testing procedures, the Berlin Numeracy Test presented harder (versus easier) question sets depending on whether participants answered the first question accurately (versus not) (Cokely *et al* 2012). We measured 'need for cognition' or motivation to solve complex problems with an established 18-item scale, which asked participants to provide 1–5 ratings in response to statements like 'Thinking about numbers is not my idea of fun' (Cacioppo *et al* 1984). Table S12 in the supplementary materials provides Pearson correlations between variables.

The data that support the findings of this study are openly available at https://doi.org/10.5518/720.

3. Results

3.1. Number of rules for identifying food with a low carbon footprint (Research question 1a)

On average, each participant generated only 1.51 rules (SE = 0.05) for the food group to which they were assigned, for a total of 949 rules across participants and food groups. The average number of rules was similar for produce ($M = 1.61$, SE = 0.09) and dairy ($M = 1.55$, SE = 0.09). Slightly fewer rules were generated by participants who focused on protein-rich products ($M = 1.38$, SE = 0.08). Number of rules was analyzed in a set of linear regression models, including individual-difference variables (table S5; tables S6(A) and S6(B) in supplementary materials). Participants with stronger environmental worldviews, more climate change knowledge, and higher numeracy generated more rules (tables S6(A) and S6(B) in supplementary materials).

These analyses relied on the first author's coding of generated rules, with the third author coding a random subset of 20% of participants (Hruschka *et al* 2004). Maxwell's (1977) coefficient for binary data, an index for interrater reliability, was $M = 0.96$ for rules generated for produce, $M = 0.98$ for rules generated for dairy and $M = 0.99$ for rules generated for protein-rich products suggesting sufficient agreement between coders.

3.2. Percent of participants generating most effective rules for identifying products with lower carbon footprints (Research question 1b)

Few participants generated the most effective rule for reducing carbon footprints for products in each food group, as identified by life cycle analyses from climate and environmental sciences (figures 1(a)–(c); table S4). Specifically, only 6% of participants who were asked about produce generated the most effective rule 'Avoid transportation by air', which according to life cycle analyses from climate and environmental sciences (table S4), is the most effective rule for identifying produce with a low carbon footprint. By comparison, 36% mentioned the most frequently generated rule for produce 'Buy local'. It was often mentioned separately from 'Avoid transportation by air'. However, in the UK, 'Buy local' implies that products were not transported by airfreight because distances are too short. The second and third most frequently generated rules for produce were 'Buy organic' (24%) and 'Reduce packaging' (16%), which, according to life cycle analyses from climate and environmental sciences (table S4), were relatively less effective for identifying produce with low carbon footprints.

Only 6% of participants who were asked about dairy generated the most effective rule according to life cycle analyses from climate and environmental sciences (table S4), namely 'Replace dairy by plant-based alternatives'. By comparison, the most frequently generated rules for dairy products were 'Buy local' (25%), followed by 'Buy less processed food' (15%) and 'Buy organic' (14%), which, according to life cycle analyses from climate and environmental sciences (table S4), were relatively less effective for identifying dairy products with low carbon footprints.

For protein-rich products, 9% of participants generated the most effective rule identified by life cycle analyses from climate and environmental sciences (table S4), which was 'Replace animal-based by plant-based products.' The most frequently generated rules for protein-rich products were the same as for dairy products: 'Buy local' (29%), 'Buy less processed food' (15%) and 'Buy organic' (15%). According to life cycle analyses from climate and environmental sciences (table S4), these rules were also relatively ineffective for identifying protein-rich products with low carbon footprints. Participants' climate change knowledge, numeracy, and 'need for cognition' were unrelated to identification of the most effective rule independent of food group; participants with higher climate change knowledge were slightly less likely to identify the most effective rule for dairy and protein-rich products, compared to produce (tables S7(A) and S7(B) in supplementary materials).

Interestingly, participants who mentioned the most frequent rule for produce, 'Buy organic', tended to evaluate this rule as slightly more effective when they had stronger environmental worldviews (correlations between perceived rule effectiveness and environmental worldview for participants who mentioned 'Buy organic' were as high as $r = 0.24$, $p = 0.09$ for produce, $r = 0.14$, $p = 0.47$ for dairy, and $r = 0.15$, $p = 0.73$ for protein-rich products). Thus, participants with stronger environmental worldviews did not always seem to know more about how to identify food products with lower carbon footprints. Although

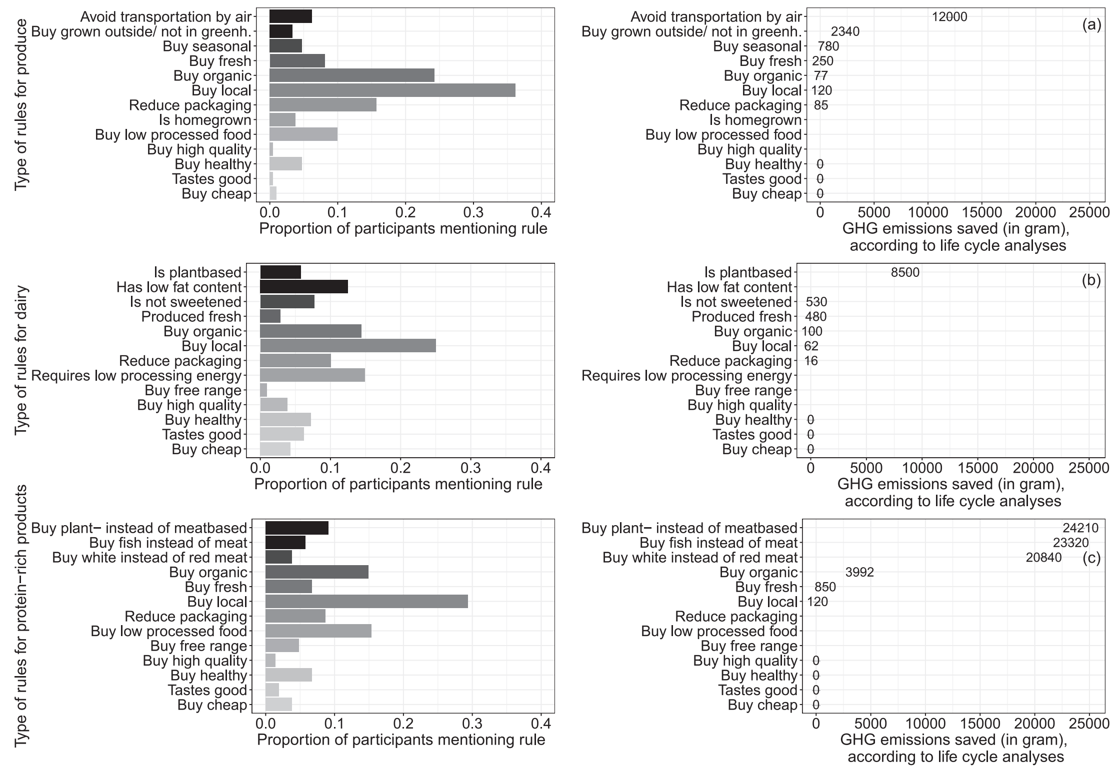

Figure 1. Types of generated rules for identifying products with low carbon footprints, proportion of participants mentioning each rule; and greenhouse gas emissions saved when applying these rules. Left panel: Proportion of participants generating each rule for each food group (X-axis; a. Produce, b. Dairy, c. Protein-rich products). Darker shading indicates that the rule is more effective for reducing GHG emissions, according to life cycle analyses from climate and environmental sciences. Right panel: GHG emissions savings associated with rules, in gram of GHG emissions, identified in life cycles analyses from climate and environmental sciences (table S4 in the supplementary materials provides associated references to the relevant literature).

these participants may shop for food with such rules in mind (Neff *et al* 2018), their rules may not be the most effective ones.

3.3. Accuracy of participants' numerical estimates of the GHG emission reductions for pre-selected rules, in grams or percentages (Research question 2)

Participants' numerical estimates of the reductions in GHG emissions associated with pre-selected rules were less accurate when made in grams rather than percentages. To allow comparisons between the estimates participants made in grams versus percentages, we transformed percentage estimates to grams. The accuracy of each participants' estimate for each rule was reflected in the mean absolute deviation (MAD; Budescu *et al* 2014, Bruine de Bruin *et al* 2017) from an estimate obtained according to life cycle analyses from climate and environmental sciences (figure 1, table S4). Accuracy was worse for estimates made in grams than for estimates made in percentages, as seen in lower mean absolute deviations ($M_{MAD} = 12786.25$, SE = 8292.27; Median = 379 versus $M_{MAD} = 1169.61$, SE = 183.17; Median = 37; $t(1200) = 1.40$, $p = 0.20$, $d_{Cohen} = 0.06$). Figure 2 suggests that the variances of mean absolute deviations were also higher when estimates were made in grams rather than percentages (F-test for variances $F(1208, 1272) = 1946$, $p < 0.001$, 95%CI [1741, 4047]). Mean absolute deviations were higher for dairy and protein-rich products, compared to produce. Participants' environmental worldviews, climate change knowledge, numeracy, and 'need for cognition' were unrelated to mean absolute deviations, independent of numerical format (tables S9(A) and S9(B) in supplementary materials).

In an auxiliary analysis, we found that participants expressed that they felt less confident when estimating reductions of GHG emissions in grams ($M = 2.37$, SE = 0.10) rather than in percentages ($M = 3.06$, SE = 0.11; $t(1, 446) = 4.48$, $p < 0.001$; 95%CI [0.39, 0.99], $d_{Cohen} = 0.40$). Higher confidence was related to less environmental worldviews, better climate change knowledge, and lower numeracy, and a slightly lower 'need for cognition' (tables S10(A) and S10(B) in supplementary materials).

4. Discussion

Our findings suggest that participants struggled to identify effective rules for reducing their food-related carbon footprints (Clune *et al* 2017, Hartmann and Siegrist 2017, Shi *et al* 2018). That is, the vast majority

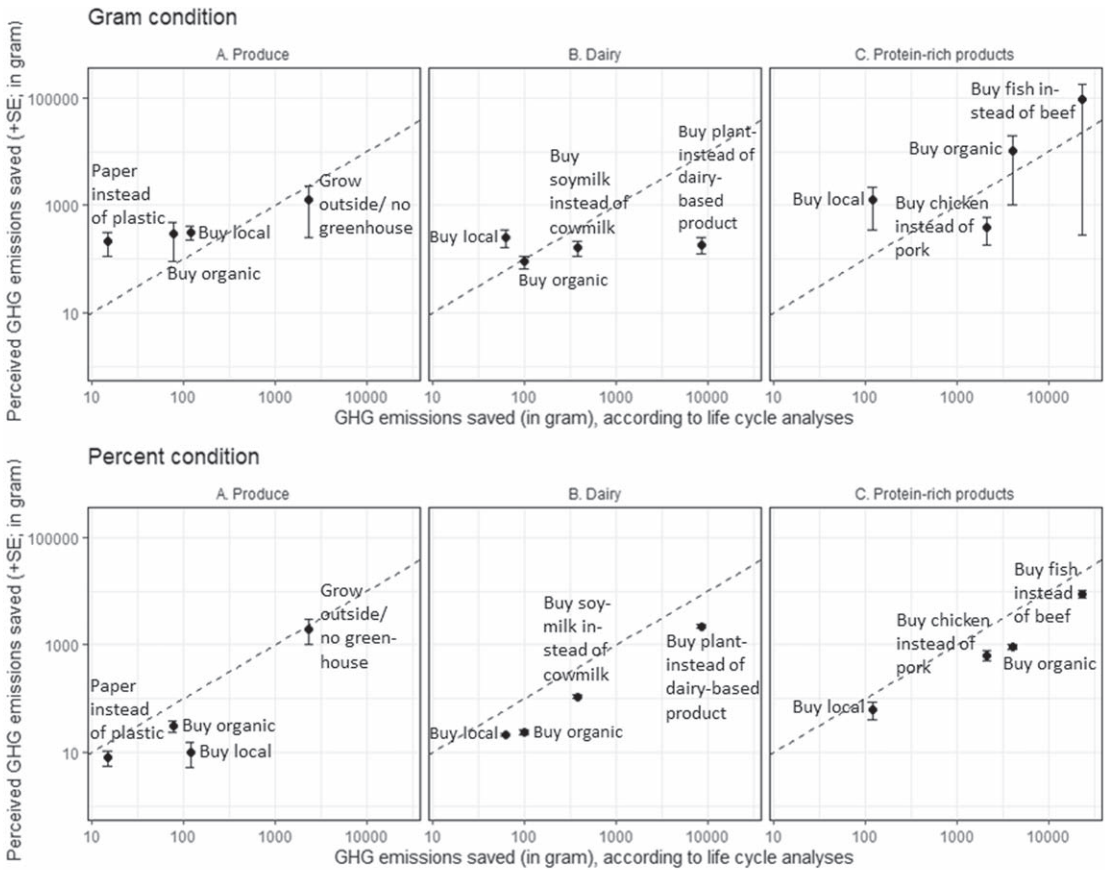

Figure 2. Participants' mean perceived numerical estimates for reductions in GHG emissions associated with four rules, in grams (upper panel) and percentages (lower panel); as compared to estimates from life cycle analyses from climate and environmental sciences, for four rules within each food group.

was unable to generate the most effective rules recommended by existing life cycle analyses from climate and environmental sciences (table S4). When being presented with rules that were pre-selected by the authors, participants struggled with correctly estimating the reductions in GHG emissions associated with each of those pre-selected rules. Their estimates of reductions in GHG emissions deviated more from estimates assessed by existing life cycle analyses from climate and environmental sciences (table S4), when participants made these estimates in grams rather than in percentages. Performance on these tasks was only somewhat related to participants higher environmental worldviews, better climate change knowledge, higher numeracy, and 'need for cognition'.

We therefore conclude that better communications are needed to help consumers to identify the most effective rules for reducing food-related carbon footprints. These communications need to express GHG emission reductions in percentages, rather than in grams. We propose five strategies on how to improve communications about effectively reducing food-related carbon footprints. These need to reflect possible reasons for participants' reliance on less effective rules for identifying products with lower carbon footprints.

First, consumers who seek to reduce their carbon footprint may benefit from food labels and associated information campaigns (Upham *et al* 2011, Vandenbergh *et al* 2011, Camilleri *et al* 2019) that communicate effective rules such as 'Buy seasonal' or 'Buy white instead of red meat'. At present, consumers may be influenced by food labels prevalent around them that encourage them e.g. to 'Buy local' or 'Buy organic' (Hertwig *et al* 2005). Those may be effective for promoting support for e.g., local and small-scale producers but they are only somewhat effective for promoting reduction of carbon footprints. Additionally, UK media reports should focus on climate impacts of food (Carrington 2018). Sustainability marketing campaigns of large supermarket chains in the UK need to promote more effective rules for reducing carbon footprints of food, rather than only 'reducing packaging' (Haward 2018, Smithers 2019).

As a result of such campaigns and media reports, consumers may also know less about specific food groups (Hartmann and Siegrist 2017). This may also explain why the overall number of rules for protein-rich products, compared to other food groups, was slightly lower: in response to recent media reports on health impacts of meat consumption, or on ineffective land use for producing animal feed for meat production (Carrington 2018), participants may have simply thought that overall, they should reduce consumption of foods rich in animal proteins without knowing about or considering plant-based alternatives such as tofu or quorn.

Second, consumers may benefit from communications that emphasize the health and environmental benefits of rules that focus on, for example, replacing meat products with tofu or quorn (Watts *et al* 2015, Scovronick *et al* 2019). Food products that have positive health impacts tend to be perceived as having positive environmental impacts as well (Gorissen and Weijters 2016, Perkovic and Orquin 2018). Some UK media reports have already linked public health concerns with land use impacts of meat consumption (Carrington 2019).

Third, consumers may benefit from being informed about rules that are applicable to more than one food group (Newell *et al* 2004). Our participants may have found a generic rule such as 'Buy organic' more appealing because it can be applied to most food groups, in contrast to more specific rules such as 'Buy white instead of red meat' or 'Buy seasonal'. Also, if our participants believed that only a small percent of food products was flown into the UK, then the rule 'Avoid transportation by air' may not have seemed useful to them. They may successfully use such generic rules, even when they know less about one food group, compared to others (Hartmann and Siegrist 2017).

Fourth, communications should focus on those rules that consumers find easiest to implement (Gardner and Stern 2008, Steg and Vlek 2009). Studies that have asked participants to generate rules for saving energy in their homes have shown that they tend to focus on rules that are less effective, but easier to implement, such as turning off the lights (Attari *et al* 2010, 2011, Lesic *et al* 2018).

Fifth, consumers may find communications about rules for reducing carbon footprints easier to understand if they are expressed in percentages rather than grams. While experts from climate and environmental sciences may prefer to communicate GHG emission reductions in grams, others may find numerical format to be abstract, complex, and unfamiliar. Such communications may be further simplified by providing consumers with a single GHG emission value that they can use for comparison (Galesic *et al* 2016, McDowell and Jacobs 2017), such as the GHG emissions associated with a medium-sized tomato (Camilleri *et al* 2019). Also, numerical formats like GHG emissions per calorie or average portion size (Camilleri *et al* 2019) might make communications about food-related GHG emissions easier to understand. Health communications use simple visualizations for communicating risks that may also be helpful in the climate domain (McDowell *et al* 2016).

One limitation of our study is that our sample was relatively highly educated. Although individuals with a college degree may have been somewhat better able to generate effective rules for reducing their food-related carbon footprint, their overall knowledge was still limited. They also did not do consistently better than individuals without a college degree, when estimating GHG emission savings for pre-selected rules. Thus future studies need to be conducted with more diverse samples. Furthermore, it remains unclear how people perceive GHG emissions across food groups, or how they think overall food-related GHG emissions compare to GHG emissions from other domains of consumption (Truelove and Parks 2012). It is not yet known how to effectively target individuals from different demographic backgrounds. Here, participants who were women, had a college degree, and were older generated more effective rules for some of the food groups, but did not make more accurate numerical estimates when asked to assess GHG emission reductions associated with different pre-selected rules. Finally, we have not yet tested how consumers respond to communication interventions about most effective rules for reducing food-related carbon footprints, in particular when those do not match their initial perceptions, and how they make actual choices about food (Siegrist & Hartmann 2019).

5. Conclusion

Our findings suggest that consumers are relatively unaware about how to reduce food-related carbon footprints. Better communications will support those aiming to reduce their carbon footprints to make choices which are in line with their aims (Attari *et al* 2010). Simple rules show great promise for helping consumers to make, fast and frugal′ choices in varying and complex contexts (Gigerenzer and Gaissmaier 2011). Communications that focus on the most effective rules for reducing food-related carbon footprints can be an efficient way to subsequently also facilitate behavior change (Truelove and Parks 2012, van der Linden *et al* 2015), among other interventions for removing contextual barriers for effective change (Todd *et al* 2012) in order to help curb anthropogenic climate change.

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