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SHORT PAPER

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Improving carbon footprint estimates of food items with a simple seeding procedure

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Abstract

Laypeople's estimates of carbon footprints have repeatedly shown to be deficient, which may hinder targeted behavior change to reduce CO_2 emissions. In an online study ($N = 127$), a vast underestimation of carbon footprints for 60 food items was observed in an on average highly educated convenience sample, confirming a lack of carbon footprints knowledge. Then, target carbon footprint values for a small subset of 15 "seeding" items were provided, which led to a large improvement in a second estimate for both the seeding as well as the remaining transfer items. A lens model analysis showed that participants adjusted the weighting of several predictors in the correct direction due to this simple intervention. It is argued that although almost 30 years old, "seeding the knowledge base" has probably been neglected as an effective low-cost intervention for improving quantitative knowledge of the public. This is especially important concerning societal problems that rely on adequate numerical knowledge for behavior regulation.

KEYWORDS
carbon footprints, environmental knowledge, numerical estimation, seeding

1 | INTRODUCTION

Greenhouse gases (GHG) are gases that trap the sun's heat in the atmosphere, which is known as the greenhouse effect. While GHG emissions come from a variety of natural sources, human activity has caused most of the increase in GHG in the atmosphere over the last 150 years, thus driving global climate change (IPCC, 2013). Carbon dioxide (CO_2) is the primary greenhouse gas emitted through human activities, accounting for around three-quarters of total emissions (IPCC, 2014). The ongoing climate crisis presents one of the world's most pressing challenges. According to the International Energy Agency, the 6% increase in CO_2 emissions has surpassed yet another record threshold in 2021, taking global greenhouse gas concentrations to their highest level in history with concentrations up 149% compared to pre-industrial levels (World Meteorological Organization, 2022).

A major contributor to the GHG emissions is the food industry. The food system as a whole—including land use, supply chain, refrigeration, and consumption—accounts for a quarter up to one third of total global man-made GHG emissions (Crippa et al., 2021; Ritchie & Roser, 2020). Different food products have a different impact on the environment. Xu et al. (2021) estimated that production-related GHG emissions from animal-based foods account for 57% of total food-related GHG emissions, whereas plant-based foods only account for 29%.

Therefore, besides regulatory political measures, behavioral strategies for reducing associated environmental impacts are required at the individual consumer level. Even though awareness of the importance of sustainability is widespread, behavioral engagement is less prevalent. Many people want to change their lifestyle to reduce their carbon footprint, but often, actual consequences of behavior in terms of CO_2 emissions are unknown or mistaken, making targeted behavioral change to reduce CO_2 emissions difficult (Kusch & Fiebelkorn, 2019; Truelove & Parks, 2012; Wynes et al., 2020). One way to reduce CO_2 emissions from food could be achieved by consumers changing their diet to a more sustainable one, which goes hand in hand with a reduction or even a full renunciation of meat consumption (Chai et al., 2019; Scarborough et al., 2014). Therefore, people must have a quantitative understanding of the environmental impacts of different types of food.

Existing research revealed that people significantly underestimate the CO_2 emissions for food, especially for meat (Camilleri et al., 2019; Shi et al., 2018). On the other hand, several studies also pointed out that consumers, being aware of the impact of meat, are willing to stop or reduce meat consumption for environmental reasons (Camilleri et al., 2019; Sanchez-Sabate & Sabaté, 2019; Truelove & Parks, 2012). The co-occurrence of "carbon innumeracy" on the one hand and a stated motivation to reduce climate impact on the other hand suggests that improving awareness of the environmental consequences of food consumption can help consumers to adopt a more responsible and eco-friendly behavior.

A better understanding of numbers and magnitudes can improve conceptualizations of various political questions, and even small amounts of information can lead to conceptual changes, especially if the provided facts are surprising (Ranney et al., 2016). The conceptual changes may increase acceptance of human-made climate change and, in turn, can lead to strengthened intentions towards action (Ranney & Clark, 2016). Thus, experimental studies investigating simple and efficient interventions to increase people's quantitative understanding of foods carbon footprint are needed.

In the study reported here, we demonstrate the usefulness of a simple procedure to improve numerical estimates that has been established about 30 years ago by Brown and Siegler (1993): These authors showed that providing a small sample of correct answers substantially improved numerical estimates in the geography domain (country populations), even for transfer items. They named the procedure "seeding the knowledge base" and assumed that feedback about an appropriate sample of items will improve the *metric* knowledge of participants, which comprises intuitions about the scale, the distribution, and common values of the target variable. Given the simplicity of the procedure and its large beneficial effects, one would expect many applications to public education. However, real-world applications of the procedure have been rare, and we conjecture that, given the low accuracy in carbon footprint estimates cited above, the seeding procedure may provide a low-cost, efficient educational procedure.

In the remainder of the article, we will first briefly review the seeding literature, followed by a brief introduction into Brunswik's lens model (Brunswik, 1952), which allows for a more in-depth analysis of how seeding affects judgments. Then, we report an online study using the seeding procedure to improve carbon footprint estimates of food items, and we will discuss the implications.

2 | SEEDING STUDIES

Brown and Siegler (1993) reported a simple intervention to improve estimates of quantities called "seeding the knowledge base." The effect was initially described in a geographic domain for estimations of countries' populations. Participants were asked to form an estimate of the populations of a certain number of countries. In the second phase, the seeding intervention was administered, which entailed the correct information for a subset of these countries' populations, the so-called seeding items. Afterwards the same country populations as in the first phase had to be estimated again. Improvements in performance were obtained for the seeding countries as well as for the untrained countries, also known as *transfer items*. Knowledge of the seeding subset obviously transferred to the remaining countries. This result was replicated by LaVoie et al. (2002) in the same domain. Concerning long-term benefits, Brown and Siegler (1996) described that even after a retention interval of 4-months the improvement of estimating the transfer countries' populations was still apparent. Hence, the seeding effect seems to be persistent and robust. The seeding effect has been successfully observed in other domains, such as estimating latitudes and longitudes (Friedman & Brown, 2000), city-to-city-distances (Brown & Siegler, 2001), automobile prices (Murray & Brown, 2009), and college tuitions (Lawson & Bhagat, 2002). Brown (2002) reported additional domains such as nutritional values of fast food and fatality rates, but the results of these studies have not been published, yet. Wohldmann (2015) applied the seeding effect to a domain relevant for behavior and demonstrated improved food choices. Participants made calorie estimates and showed transfer to new items, but only for simple foods like apples and not for complex foods like apple pie. Groß et al. (2022) recently showed improved estimates of sugar content in food items through seeding. These findings show remarkable relevance for health and prevention aspects and possible implementations to support behavioral changes.

Quantitative estimates in general require two independent components, Brown (2002) calls *metric* and *mapping* properties. Metric knowledge comprises knowledge about the scale and distribution of values whilst mapping knowledge basically reflects the rank order of stimuli along the scale. Brown and Siegler (2001) interpret the effectiveness of the seeding effect by the development of a more accurate metric knowledge within the domain.

In seeding studies, metric knowledge is assessed by the *Order of Magnitude Error* (OME) that quantifies the deviation of true value and judgment as the absolute difference between the common logarithms of both values. Using the logarithm prevents extreme outliers in statistical comparisons. The *signed* OME also bears information about the trend to under- or overestimate. Hence, a signed OME of $+1/-1$ refers to a 10-fold over-/underestimation, respectively. Mapping knowledge, on the other hand, is reflected in the correlation between judgments and true values. Both measures are partly independent. For example, as will be shown below, people have a good intuition about the rank order of food items concerning their carbon footprints, but their absolute estimates deviate very strongly from the correct value.

Given the simplicity of the procedure and its large beneficial effects, the authors concluded that "seeding the knowledge base provides an instructional technique for improving estimation that again should be applicable in a broad range of real-world contexts" (Brown & Siegler, 1993, p. 529). This promise, however, has not been fulfilled, yet with the notable exception of Wohldmann's (2015),

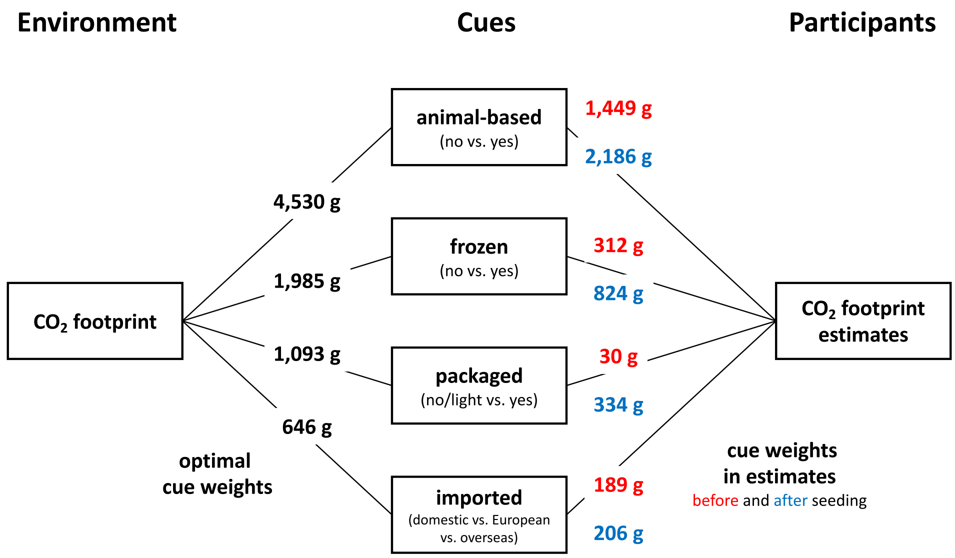

FIGURE 1 A schematic representation of the lens model. The left side ("environment") shows the optimal weighting of four cues to predict the actual CO_2 footprints of the 60 food items, determined by a linear regression (Note that the unit "grams" is specific for the target dimension used here and does not generally apply to cue weights. The regression weights express the mean change in the CO_2 emission per kg food with each one-unit change in the corresponding predictor). The right side ("participants") shows the mean weighting of the cues in participants' estimates before (upper numbers) and after (lower numbers) seeding. All cue weights except "imported" are adjusted significantly in the correct direction (although insufficiently).

Wohldmann and Healy's (2020) and Groß et al.'s (2022) application to nutritional values of food as a highly relevant domain in terms of public health.

3 | ASPECTS OF JUDGMENT ACCURACY: THE LENS MODEL

Estimating carbon footprints is basically a "Brunswikian" judgment task under uncertainty: According to the lens model by Egon Brunswik (1952), people view a to-be-judged criterion variable through a "lens" of accessible cues, which are statistically related to it. As Murray and Brown (2009) have shown for estimates of automobile prices, participants may decompose items into sets of cues (they call features) and generate estimates by weighing the cues appropriately. In their seeding study, providing a few seed items resulted in improved cue weighting.

Figure 1 shows the typical schematic presentation of the lens model that allows for characterizing the environment (actual CO_2 footprints) and the judgments (CO_2 footprint estimates) as dependent on a set of cues. A regression analysis of the actual footprints (left side of the lens) provides optimal cue weights and hence, an optimal way of linearly combining the cues for predicting the CO_2 footprints. On the participant side of the lens, a corresponding regression analysis of the observed estimates measures the *cue utilization*, that is, the weights given to the cues by the judge. It is obvious that the overall performance as measured by a correlation r_a between estimates and true values (i.e., mapping knowledge) will depend on the match between the optimal weights and cue utilizations. The better both sets of weights correspond, the higher the correlation will be. However, the multiple correlations R of both regression analyses put an upper bound on the possible r_a values, even if the match between cue weights on both sides of the lens were perfect.

Hence, using the regression approach, it is possible to compare both sets of weights before and after seeding in order to see whether the intervention also improves the weighting of available cues. This will allow a more fine-grained view of possible improvement in mapping knowledge due to seeding. Without going into detail here, we will also use the *matching index G* derived from Tucker's (1964) lens model equation that represents the overall match between the set of weights in a single number (see Karelaia & Hogarth, 2008; Tucker, 1964, for details). In addition, we can assess whether seeding improves the consistency of the judgments as measured by the multiple correlation between cues and estimates.

4 | GOAL AND RESEARCH QUESTIONS

The main goal of the current study was to evaluate whether a simple intervention like "seeding the knowledge base" would improve judgments in a highly relevant behavioral domain. This is not self-evident since most former applications used judgment criteria with much larger ranges (population sizes, geographical distances). However, building on the former studies, we aimed at a confirmatory test of the hypotheses (1) that seeding will improve CO_2 footprint estimates for both seeding items as well as transfer items and (2) that the effect is stronger for the former than the latter. As an additional explorative question, we conducted a lens model analysis in order to explore whether beneficial effects of seeding (a) extend to mapping knowledge and (b) affect judgmental consistency or rather the appropriate weighting of predictors. As a second exploratory question, we wanted to see how the CO_2 footprint estimates and their potential improvement are influenced by knowledge about environmental issues.

5 | METHOD

5.1 | Design

The study used a 2 (timepoint: before vs. after seeding) by 2 (item type: seed vs. transfer) within participants design with an additional counterbalancing factor of seed item set (four factor levels) varied between participants.

5.2 | Materials

Sixty food items were selected from the list by Reinhardt et al. (2020), spanning a range from 100 g CO_2/kg (carrots) to 13,600 g CO_2/kg (beef) from different food categories. Four exclusive and exhaustive sets of seed items were generated for the counterbalancing factor that were as parallel as possible in the range of CO_2 values and number of items per food category (see Appendix A: Table A1). Environment-specific knowledge was assessed with 17 highly relevant items[1] from the "Environmental Knowledge Test (EKT)" by Geiger et al. (2019). The advantage of this measure is that it actually tests knowledge rather than just assess self-reports. The authors report high correlations of the full scale ($r = .77$) with general knowledge, and acceptable reliability of $\omega = .74$ as estimated with a structural equation model.

5.3 | Procedure

The experiment was conducted as an online questionnaire. First, participants were asked to estimate the carbon footprint of 60 food items. One example that was not included in the task (cucumber, 400 g CO_2/kg), was given for familiarization with the answering format. The items were displayed individually and in a randomized order for every participant. In each trial, the name of the food item was given, followed by an open text field to fill in the carbon footprint estimation for this specific food item. Once all items had been completed, one randomly assigned seeding set, containing the correct carbon footprint values for a quarter of the items, was shown. In addition, participants received the instruction to memorize these presented numeric facts, which were presented successively as well. Afterwards, all 60 food items were estimated a second time, in the same manner as before. The experiment concluded by assessing environmental knowledge with the 17 selected EKT items (Geiger et al., 2019).

5.4 | Participants

Initially, 211 students of the University of Mannheim and acquaintances of the experimenters (friends, colleagues, family, and fellow students) were recruited for the experiment through personal communication, the university's mailing list, and the psychology department's online participant recruitment system. None of the participants were aware of the study's hypotheses or goals. Altogether, 84 participants were excluded from data analysis due to various reasons. The majority either did not start the experiment (41 people) or did not complete the first round of estimations (37). Other causes were not finishing the second round of estimations (3), giving nonsensical answers, misunderstanding the instructions or being less than 18 years old (one person each). Hence, this study's final sample consisted of 127 participants (56.7% female, 1 person identified as diverse) with a mean age of 30.67 ($SD = 13.99$). Most participants either had a high school diploma (33.1%) or a university degree (50.4%). Most participants were university students (66.14%) or enrolled in non-academic job training (2.36%). 25.2% were employed or working in their own business, and 6.29% responded "other" regarding their current occupation.

6 | RESULTS

6.1 | Data preparation

Because of the response format using open text fields, several estimates contained non-numerical characters like "g" or "kg" or commas and decimals. Easily interpretable entries (e.g., "400 g" or "1.5 kg") were recoded accordingly. Uninterpretable entries like "E333" were discarded. Hence, 19 data points (0.12%) were missing and 154 data points (1.01%) were recoded. All recoding is documented in the corresponding file at the OSF supplement.

6.2 | Accuracy of carbon footprint estimates and seeding effect

Figure 2 presents the full distributions of estimates in terms of signed OME given before seeding (red) and after seeding (blue) separately for seeding items and transfer items. Because of the extreme right-skewed distributions (there is much more room for over- than underestimation) and to avoid arbitrary exclusion criteria, we report the medians as central tendency: People tended to underestimate the actual carbon footprints in their first estimate by 37.5 and 41.18 percentage points for transfer and seed items, respectively. After seeding, however, the median of estimates exactly matched the true values for both item types (0 percentage points underestimation).

We conducted a two-factorial repeated-measures ANOVA on the mean OME values of the 127 participants. The main effect of time point was large and highly significant, $F(1, 126) = 90.33$, $p < .001$,

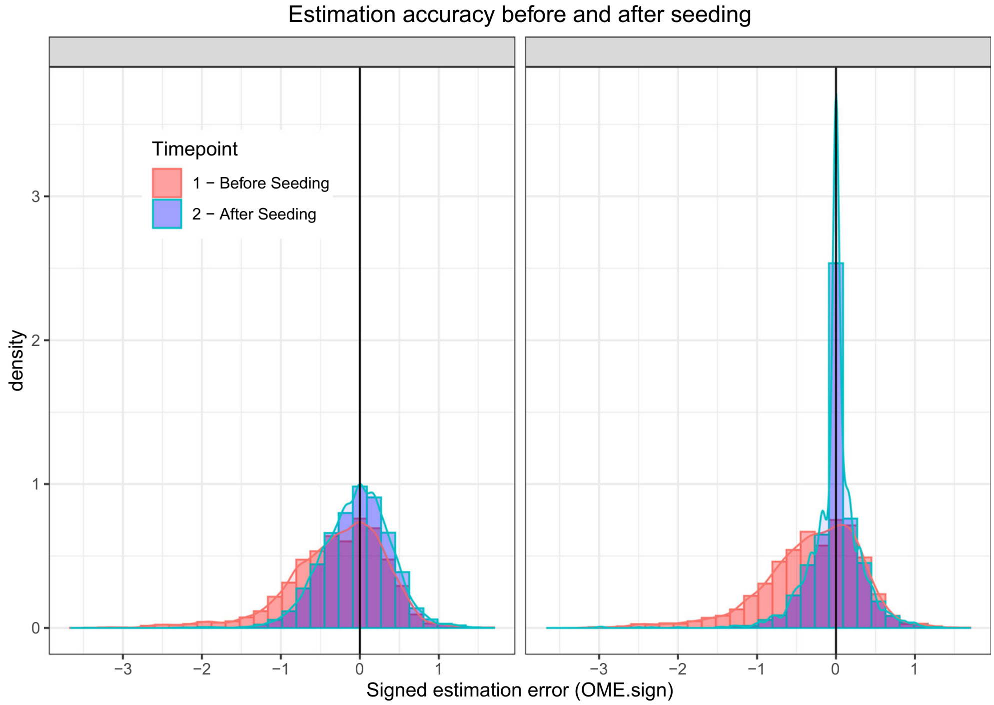

FIGURE 2 Distribution of signed order of magnitude error for transfer (left) and seed items (right) before (red) and after seeding (blue). Note the logarithmic *x*-axis: "+1" and "−1" refer to a 10-fold over- or underestimation, respectively.

$\eta_p^2 = .42$ as was the main effect of item type, $F(1, 126) = 91.94$, $p < .001$, $\eta_p^2 = .42$. The interaction was also significant, $F(1, 126) = 248.99$, $p < .001$, $\eta_p^2 = .66$, showing a larger effect for seed items than transfer items. Importantly, the time point effect was also present if transfer items were analyzed separately, $t(126) = 6.71$, $p < .001$. Hence, both hypotheses about the seeding effects were confirmed. Note that the main effect of time point was robust for all dependent variables measuring metric accuracy (OME, signed OME, absolute deviation, simple deviation) and different individual aggregations (mean, median).[2]

6.3 | Lens model results

Whereas the deviation measures reflect "metric" knowledge according to Brown (2002), the "mapping" knowledge is assessed via the correlation between judgments and correct values that mainly cover the correct rank ordering of items. Restricting the analysis to the transfer items, we found an increase in the mean correlation from $r = .58$ to $r = .63$ (medians $r = .61$ and $r = .69$, respectively) from the first to the second estimate, which was significant according to a Wilcoxon signed rank test, $V = 2307$, $p < .001$.

In order to analyze the source of this improvement in mapping knowledge further, we coded four obvious and readily available predictors of carbon footprint for the 60 food items: (1) animal product (yes = 1 vs. no = 0), (2) packaged product (yes = 1 vs. no/light plastic or paper = 0), (3) imported (no = 0, typically European = 1, typically overseas = 2), and (4) frozen (yes = 1 vs. no = 0). We chose these variables because they explain 58% of carbon emission variance in our sample of 60 items and are potentially available to the participants

TABLE 1 Mean (and SD) of lens model parameters before and after seeding for transfer items.

	Before seeding	After seeding
r_a	.58 (0.17)	.63 (0.18)
G (matching)	.86 (0.21)	.90 (0.12)
R^2_{judge} (consistency)	.41 (0.14)	.43 (0.16)

from general knowledge. From the description of the products it was clear whether they were fresh or processed (see Appendix A: Table A1), and we contrasted explicitly mentioned or typical packaging (can, glass, and beverage carton) with typically no or light plastic packaging (fresh fruit and vegetables) as customary in German supermarkets.

Applying the lens model to the data of the transfer items, we assessed for each participant the matching index *G* and judgment consistency R_{est}, for initial and post-seeding estimates. Comparing the parameters with paired Wilcoxon tests, we found a significant increase ($p < .05$) in the matching index *G*, but not in the consistency R^2 ($p = .09$). Matching was already very high before seeding, and all parameter increases were numerically small (see Table 1).

To illuminate the matching effect in *G* further, one can also look at the cue utilizations, that is, the regression weights of the cues when analyzing the estimates. These can be compared to the optimal weights in our sample of food items. As can be seen in Figure 1, all predictors except "Import" received larger weights after seeding (all other changes $p < .001$ according to Wilcoxon signed rank tests for transfer and seeding items). The weights given to the cues were still smaller than the optimal weights, but seeding obviously had a positive effect on the adequate weighting of the four predictors.

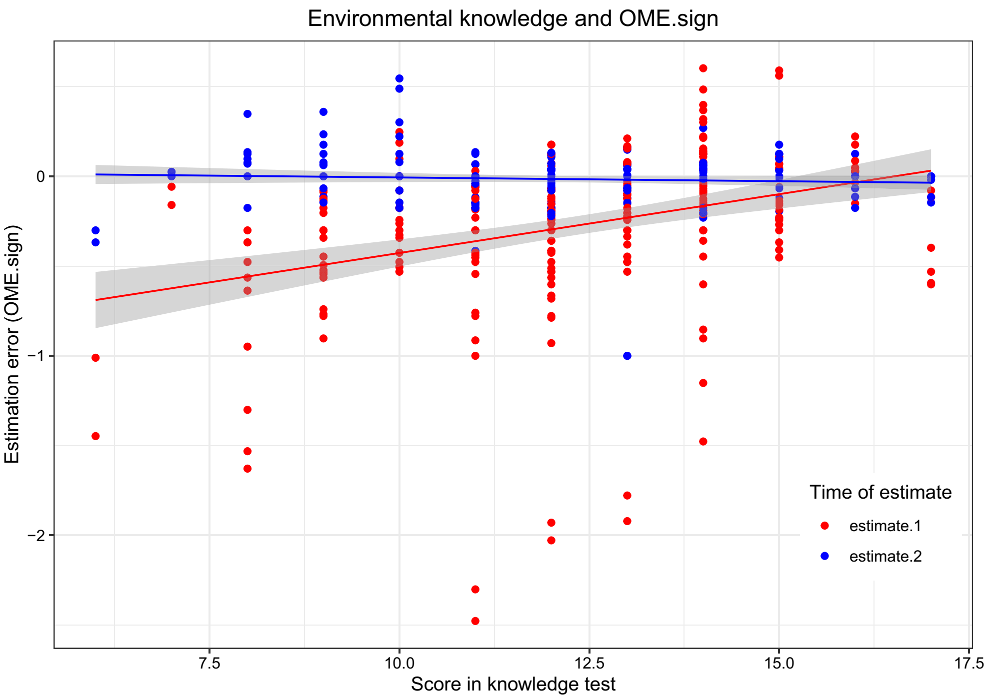

FIGURE 3 Relation between underestimation depicted by the signed order of magnitude error (OME) and knowledge test results before (red) and after (blue) seeding (transfer items only).

6.4 | The role of general environmental knowledge

To assess the relation between pre-existing environmental knowledge and judgment accuracy as well as its improvement, we calculated a multilevel regression with timepoint (effect-coded as -0.5 and $+0.5$) and the EKT score (sum of correct answers across the 17 items, centered) as well as their interaction as predictors. To avoid spurious effects due to simple memorization, we restricted the analysis to the transfer items. We analyzed both individual mean OME and the individual mean of the signed OME as dependent variables, the latter one depicted in Figure 3. Timepoint significantly reduced OME ($\beta = 0.40$, $t(124) = 24.09$, $p < .001$) and increased signed OME ($\beta = 0.26$, $t(124) = 7.89$, $p < .001$), reflecting the seeding effect that reduced absolute error and remedied the vast underestimation in Estimate 1. Knowledge was also related to both accuracy measures, $\beta = -0.026$, $t(124) = -3.48$, $p < .001$ and $\beta = 0.028$, $t(124) = 2.94$, $p = .004$, respectively. Finally, the interactions were significant as well, $\beta = 0.025$, $t(124) = -2.318$, $p = .022$ for OME and $\beta = -0.071$, $t(124) = -4.83$, $p < .001$ for signed OME. The interaction is easiest to interpret when looking at the signed OME scores in Figure 3: Lower scores in the knowledge test were associated with larger underestimation errors in the first estimates (red line, $r = .33$), whereas the correlation with prior environmental knowledge essentially vanished in the second estimate (blue line, $r = -.07$), implying that participants with lower knowledge benefitted more from the seeding intervention.

Note, that the internal consistency of our EKT measure was quite unsatisfactory in our sample (Cronbach's $\alpha = .52$). This, however, would attenuate any effect, which we nevertheless observed.

7 | SUMMARY AND DISCUSSION

Despite the prominent role the climate crisis currently plays in the media, we replicated a lack of knowledge concerning carbon footprints of consumer goods in a quite educated convenience sample. There was a large variation in the estimates, and the median judgment underestimated the correct value by 37.5%. However, we also found a substantial beneficial effect of “seeding” the criterion knowledge of a fraction of items: The estimation error was very much reduced, not only for seeding items, but—importantly—also for transfer items. The medians for both item types matched the correct values in the second judgment, although variability was still high. A lens model analysis provided evidence that mapping knowledge also slightly improved, which was attributable to a more adequate weighting of important predictors. Typically, seeding effects have been restricted to an improvement in metric knowledge. Mapping knowledge improvements often only concern the seed items, but not transfer items (e.g., Groß et al., 2022). However, Murray and Brown (2009, Exp. 2) showed improved weighting of features in their automobile price estimations after seeding. In contrast to other domains investigated they observe that “consumer products are one domain that is explicitly, and intentionally, organized by features” (p. 232). If the feature structure is transparent and cues are highly diagnostic, optimal conditions for abstracting appropriate weights to improve mapping knowledge may be present. We speculate that this is also the case for our set of food items that show a clear and simple category structure as defined by the four features we used in the lens model. The generality of this claim must be tested in future work, however.

General knowledge about environmental issues as measured with Geiger et al.'s (2019) EKT scale was moderately predictive both of the estimates as well as the improvement. In our case, participants with lower test scores improved more due to seeding, which is plausible, given that they show more room for improvement.

The size of the beneficial effect of seeding in this domain surprised us both in absolute terms (median of 37.5% vs. 0% underestimation before and after seeding, respectively) as well as in effect size terms (the time point explains 18% of variance in all estimation data). Hence, we conclude that the cost–benefit-ratio for seeding-based interventions may indeed be very favorable if considered as a public education tool. Whether this is also the case for other highly relevant domains in which people might have better preexisting knowledge (such as nutritional values of foods, for example), remains to be tested, but lab studies by Wohldmann (2015) and Wohldmann and Healy (2020) in this domain provide reasons for optimism. Hence, one can conceive of more large-scale campaigning efforts in social media for the general public or targeted interventions for specific groups like diabetics.

Of course, the current study faces several limitations. To be useful, the method should have long-lasting beneficial effects on people's knowledge. Although we did not test this here, other studies demonstrated substantial temporal stability of seeding effects over 4 months for country population estimates (Brown & Siegler, 1996) or at least 1 week for nutritional information (Wohldmann & Healy, 2020). Hence, although this remains to be confirmed empirically, there is reason for optimism that effects are stable.

A second limitation of our study may be the unrepresentative and rather highly educated sample investigated. At first glance, this may question whether the results hold in more representative samples. However, given the knowledge test results, which showed a larger improvement for *less knowledgeable* participants, we may expect even larger seeding effects with larger variance in environmental knowledge. Hence, our convenience choice of an educated sample may even be a conservative test of the seeding effect.

We also did not examine potential effects on consumption behavior. The purpose of this study was to find out if seeding fosters correct carbon footprint estimations but not whether is also leads to a change in behavior. In fact, prior research indicated that an increase in knowledge can cause more environmentally friendly behavior (Camilleri et al., 2019; Sanchez-Sabate & Sabaté, 2019; Truelove & Parks, 2012) but does not necessarily have to. An "attitude-behavior" gap has been documented repeatedly in this domain (e.g., Wiederhold & Martinez, 2018), and an intervention improving better estimates of climate-relevant quantities was not accompanied by shifts in climate attitudes in a study by Thacker and Sinatra (2022). In addition, the latter authors warn about a potential backfire effect, particularly in polarized topics. Thus, the effect of seeding on purchase decisions in the climate change domain needs to be investigated further and more motivational and behavioral effects as well as their interactions need to be considered (see Ranney et al., 2016).

Finally, the study was not preregistered although we had clear hypotheses. Despite this omission by the authors, we nevertheless think that the results are trustworthy because they were robust across various analyses (ANOVAs, *t*-tests, Wilcoxon-tests) and dependent variables measuring judgment error (OME, signed OME, simple absolute and signed deviation).

8 | CONCLUSION

Although advocated as a potentially powerful instructional technique for a "broad range of real-world contexts" about 30 years ago, such applications of the seeding procedure have been rare. As our data show, large beneficial effects may be achieved with this inexpensive, low-threshold method, which we hope to be acknowledged by public educators, especially in areas requiring a numerically informed public, such as the desperately needed reduction of CO_2 emissions.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Raw data and analysis files are available at https://osf.io/wqx8t/.

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ENDNOTES

[1] Subscales "climate" (Items 6–10), "resources" (11–14) and "consumption behavior" (15–23) in Geiger et al. (2019). Example items in 4-alternative forced choice format are, respectively, "Which energy form is a renewable form of energy? (nuclear energy, petroleum, natural gas, and *geothermal energy*)," "For which material does recycling save the most energy compared to new production? (*aluminum*, glass, tinplate, and paper)," and "Which type of transport produces the least amount of emissions per passenger and kilometer in short distance traffic? (*tram, subway & urban train*, car, and public transit bus).

[2] All effects for OME also replicated in all four counterbalancing item sets except Set 1 in which the item type main effect was not significant, $F(1, 33) = 2.96$, $p = .095$. With other dependent variables, the item type effect or interaction were not significant in all cases, but the time point effect was robust. All ANOVA results are available on https://osf.io/wqx8t/.

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APPENDIX A

TABLE A1 Sixty food items in four counterbalancing seeding sets with CO_2 footprint in kg per kg food source.

Set 1		Set 2		Set 3		Set 4	
Peach, fresh	0.2	Potatoes	0.2	Zucchini	0.2	Carrots	0.1
Pumpkin	0.2	Onion	0.2	Cauliflower	0.3	Eggplant	0.2
Oat drink	0.3	Pear	0.3	Broccoli	0.3	Orange	0.3
Ruccola	0.3	Brussels sprouts	0.3	Grapes	0.4	Strawberries	0.3
Apple	0.3	Gnocchi	0.6	Oatmeal	0.6	Banana	0.6
Bread	0.6	Bell pepper	0.6	Avocado	0.6	Soy yoghurt	0.6
Spinach, frozen	0.6	Fries, frozen	0.7	Asparagus	0.7	Pasta	0.7
Beans, fresh	0.8	Pineapple, fresh	0.9	Tofu	1.0	Tomato, fresh	0.8
Lentils	1.2	Mushrooms	1.3	Chickpeas (can)	1.3	Vegan Patty	1.1
Vegan Sausage	1.7	Passed tomatoes	1.8	Beetroot (glass)	1.3	Corn (can)	1.2
Curd	3.3	Egg	3.0	Milk	1.4	Linseed	1.4
Chocolate	4.1	Olive Oil	3.2	Peas (can)	1.7	Yoghurt	1.7
Tomato puree	4.3	Porc	4.6	Rice	3.1	Honey	2.0
Fish, aquaculture	5.1	Chicken	5.5	Cream	4.2	Cheese	5.7
Butter	9.0	Feta cheese	7.0	Shrimps, frozen	12.5	Beef	13.6

Note: Carbon footprint estimates were provided in g/kg in the experiment.
Source: Reinhardt et al. (2020).