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Testing the impact of overt and covert ordering interventions on sustainable consumption choices: A randomised controlled trial

Shi Zhuo [a,*], Michael Ratajczak [a,b], Katie Thornton [a], Phil Jones [c], Ayla Ibrahimi Jarchlo [c], Natalie Gold [a,d]

[a] Behavioural Practice, Kantar Public UK: 4 Millbank, London, SW1P 3JA, United Kingdom
[b] Department of Linguistics and English Language, Lancaster University, LA1 4YL, United Kingdom
[c] Social Science Team, Food Standards Agency: Clive House, 70 Petty France, London, SW1H 9EX, United Kingdom
[d] Centre for Philosophy of Natural and Social Science (CPNSS), London School of Economics, London School of Economics and Political Science, Houghton Street, London, WC2A 2AE, United Kingdom

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ABSTRACT

Food products have significant impacts on the environment over their life cycle. We investigated whether displaying products in ascending order of carbon footprint in an online supermarket environment can shift consumer choices towards more sustainable options. We examined whether the effect of the ordering intervention differs when the ordering is overt (information about the ordering is explicit), compared to when it is covert (participants not told about the ordering). We conducted a three-arm parallel-group randomised trial using 1842 online participants from England, Wales, and Northern Ireland. Participants shopped for a meal, choosing one product from each of six product categories in a simulated online supermarket. Six products were listed vertically on each product-category page. Products were randomly ordered for the control arm but ordered by carbon footprint in the covert and overt ordering arms. In the overt ordering arm, a statement was displayed at the top of each product page about the ordering of products. The primary outcome was whether one of the three most sustainable products was chosen in each product category. There was no effect of the covert ordering on the probability of choosing more sustainable products compared with the control arm (OR = 0.97, 95% CI 0.88–1.07, p = 0.533). Furthermore, we did not find evidence that the effects of the covert ordering and overt ordering differed (p = 0.594). Within the control condition, products in different positions were chosen with similar frequencies, suggesting that product positioning does not have an impact on choices. This may explain why re-ordering products had no effect. In the overt condition, only 19.5% of people correctly answered that the products were ordered according to sustainability in a follow-up question, suggesting that they didn't notice the statement. Results suggest that choices for grocery products might be too ingrained to be changed by subtle rearrangements of choice architecture like the ordering interventions, and highlight the difficulty of conveying information effectively to consumers in the online grocery shopping environment.

1. Introduction

1.1. Background

The production, transportation, storage, and waste of food products have a significant impact on the environment. The UK government's National Food Strategy, an independent review of England's entire food system, recommends that multiple interventions are required for healthy and sustainable diets to create a long-term shift in our food culture (Dimbleby, 2021). To reduce the environmental impact of the food supply chain, consumers need to be able to access a more sustainable diet. The environmental impact of food is also concerning for consumers. For example, 73% of 1916 surveyed adults, in a study commissioned by the Food Standards Agency (FSA), reported that it is important for them to buy food that has a low environmental impact (Heard & Bogdan, 2021, p. 15). However, only 49% of those consumers considered their personal diet to be environmentally sustainable. The discrepancy between consumers' concern for the environmental impact

* Corresponding author.
E-mail addresses: shi.zhuo@kantar.com, zhuoshi123@gmail.com (S. Zhuo).

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of food and the reported sustainability of their personal diets indicates that there is a need for interventions that can help consumers to access more sustainable products.

Online supermarkets constitute an increasingly large share of grocery shopping. In December 2020, 59% of shoppers reported having used online shopping for food and groceries in the previous month, an increase on the 42% who claimed that in December 2019 (Maynard, 2021). This trend of increasing online shopping was already observed before the coronavirus pandemic (Food Standards Agency, 2019, p. 96). Further, the growth is forecast to continue, with the Institute of Grocery Distribution projecting that the market value of online food and grocery shopping will grow by approximately 21.4% in the next five years (The Institute of Grocery Distribution, 2021). Therefore, it is important to understand how interventions in online shopping environments affect consumer choices in relation to the sustainability of products.

Changing the choice architecture or the physical environment in which a decision is made, i.e., "nudge", has been used to encourage healthier diets (Ensaff, 2021). It is also increasingly being applied to sustainable diets: evidence reported in a systematic review of interventions on encouraging sustainable diets indicates that physical (in-store and in-canteen) interventions that target automatic non-conscious processes are likely to be effective (Blackford, 2021). Critically, behaviours around purchasing and consumption of food may be habitual, so targeting those behaviours could involve changing the situation that triggers the habitual behaviour or inhibiting the habitual response (Riet et al., 2011).

One type of intervention that has been effective at promoting healthy consumption in physical food-purchasing environments is altering the positioning of items: a meta-analysis of 15 comparisons from 12 studies found that when food was placed further away there was a moderate reduction in its consumption (Hollands et al., 2019). In addition, evidence was found for an order effect regarding the positioning of options on physical menus: when healthier items were placed at the top of lists, they were more likely to be chosen (Dayan & Bar-Hillel, 2011; Mueller et al., 2020). Ordering has also been used to help people make healthier choices when displaying products in digital environments (Koutoukidis et al., 2019). It seems unlikely that there is a unified explanation of position effects across different types of tasks, but some causes that are likely to be common across tasks are that people choose positions that are more reachable and positions that are more salient, especially if the incentive structure directs them towards those positions (Bar-Hillel, 2015). In a digital environment, we hypothesise that the item at the top of the list is most reachable and salient, as automatic processes lead consumers to look at products sequentially in the order they are displayed and stop at the first satisfactory product (satisficing) to expend least effort (Caplin et al., 2011).

In contrast to healthy eating, there is a research gap on the effect of ordering food products by their environmental impact on consumer choices when shopping online. Nonetheless, evidence indicates that putting the most sustainable item at the top of a hard-copy menu is associated with an increase in sustainable food consumption in workplace canteens, hospitals, and educational settings (Langen et al., 2022). Consequently, it is of interest to investigate whether using product ordering can increase the choices of sustainable products in an online supermarket environment.

'Ordering' interventions are typically implemented without telling participants that the items have been ordered in a manner designed to influence their choices. One general criticism of nudges is that they are manipulative because people do not know that they are being nudged (Goodwin, 2012; Noggle, 2018; Oliver, 2013). Some researchers argued that this lack of transparency was essential for the success of nudges (Bovens, 2009). However, there is now a growing number of studies investigating the effect of disclosing to people that they are being nudged, which show that this claim is unlikely to be correct. A systematic review found that only two out of the 87 tests covered showed a negative effect of disclosure (Bruns & Paunov, 2021). Further, being transparent about nudges can increase the feeling of autonomy of those being nudged (Wachner et al., 2020). In contrast, revealing nudges only after the event can lead to negative perceptions of the 'choice architect', who is doing the nudging (Michaelsen et al., 2021).

Studies on the effect of disclosure of nudges have mainly involved informing people that they are being given a default option (e.g., Bruns et al., 2018; Loewenstein et al., 2015; Paunov et al., 2020). Some studies of disclosure were designed to increase the choice of sustainable options (Bruns et al., 2018; Steffel et al., 2016). Two studies showed that disclosure does not decrease the effectiveness of nudges designed to promote healthy eating by making healthy items more accessible in a bricks-and-mortar environment (Cheung et al., 2019; Kroese et al., 2016).

However, as far as we are aware, no studies have investigated whether disclosure affects the effectiveness of nudges that use the ordering of items on a menu. This is particularly relevant for online shopping. In online shopping, there is always some ordering by default, which is often by popularity. There is often also the possibility of ordering the products in other ways, including by price. If an 'overt' sustainability ordering, where consumers know that products are presented in order of sustainability, is as effective as a covert one at increasing sustainable consumption, then online supermarkets could consider setting the sustainability ordering as the default with explicit information on how the ordering is generated, replacing the current default ordering.

1.2. Objectives

In this study, we investigated the effect of an ordering intervention on product choice using a randomised controlled trial. Specifically, we showed products in a vertical list with an ascending order of products' carbon footprint (from lowest carbon footprint/most sustainable to highest footprint/least sustainable), and we examined the effect of this ordering on product choices in an online supermarket environment. In addition, we compared the effect of an ordering intervention that was covert, where no information about the ordering was given, to an ordering intervention that was overt, where a statement with information about the ordering was displayed.

We aimed to test the following two hypotheses.

Hypothesis 1. A covert ordering intervention can shift consumer choices in an online supermarket environment towards more sustainable options compared to when products are randomly ordered.

Hypothesis 2. Making an ordering intervention overt does not affect the choice of sustainable options compared to when the ordering intervention is covert.

2. Methods

2.1. Trial design

An online experiment was conducted with a three-arm between-subjects design. Participants were randomly assigned with equal probability to one of the three arms: control (random ordering), covert (sustainability) ordering, overt (sustainability) ordering. Participants were asked to shop for a meal for two, making six product choices (one product from each of the six product categories), in a simulated online supermarket environment, given a budget for shopping high enough to cover the cost of selecting the most expensive products on the list. The products were chosen from the range available in the online grocery store of a major retailer. To incentivise participants to choose their most preferred products and to ensure that they were price sensitive, as price is the most influential driver of shopping behaviour (Osman & Jenkins, 2021), participants were given the option to enter a prize draw where 10 randomly chosen participants would get a delivery of the items that they chose plus any change from the budget.

In the control (random ordering) arm, products in each product category were randomly ordered. The random order was generated by the computer program for each participant independently, and for each product category independently. In the covert ordering arm, products in each product category were listed in the order of most sustainable to least sustainable, but no information about this ordering was given to the participants. In the overt ordering arm, products in each product category were listed in the order of most sustainable to least sustainable, and a statement was shown in a box at the top of each product category page to reveal this ordering to participants. The statement said “The products on this page have been ordered from the most environmentally sustainable to the least environmentally sustainable. This is to make it easier for you to choose a more sustainable product if you wish.”. Other than these differences, the three experimental arms were the same.[1]

The sustainability rank of products in each category was based on the data provided by the web browser extension Envirofy (Shakeri & McCallum, 2021). Envirofy calculates the carbon footprint of products by adding the CO_2 emitted during production, transportation, and packaging of the product. The web browser extension gave the calculated CO_2 for products in the online grocery store of a major retailer. We used it to generate an ordered product list from lowest to highest carbon footprint, which was implemented for the covert ordering and overt ordering experimental arms.

2.2. Participants and randomisation

The target population for this trial was online grocery shoppers who are aged over 18 in England, Wales, and Northern Ireland (Scotland was excluded as it is not covered by the FSA). As no official statistics were available on the specific demographic breakdown of online grocery shoppers in the targeted areas, we used quotas plus screening questions to get a sample close to a representative sample of the target group. Firstly, demographic and geographical quotas (see Online Appendix Table A1) based on the population estimates for England, Wales and Northern Ireland were imposed. Secondly, potential participants were asked about their frequency of online grocery shopping as one of the qualification questions (along with demographic questions to implement quotas) and those who chose “never” to the question were excluded.[2]

Participants were recruited through the online panel provider Lucid. Multiple quality checks were embedded in the experiment including checking for consistency of responses to equivalent questions, unusual or implausible answers to certain questions, completion time that was unreasonably short, or whether the same response was given to a block of questions. Participants who failed the quality checks were removed from the final sample. Participants were paid the standard panel provider points for completing the experiment conditional on passing the quality checks. Participants who passed the qualification stage were randomly allocated with equal probability to one of the three experimental arms.

Table 1
Optimal model for primary outcome.

Predictors	More sustainable product chosen		
	Odds Ratios	95% CI	p
(Intercept)	1.52	1.28–1.81	**<0.001**
Overt ordering[a]	0.97	0.88–1.07	0.533
Covert ordering[a]	1.00	0.90–1.10	0.931
Eat Meat: No	1.16	1.01–1.32	**0.033**
Higher Education: Yes	0.91	0.83–0.99	**0.028**
Age (Standardized)	0.88	0.85–0.92	**<0.001**
Total household income (Standardized)	0.96	0.92–1.00	**0.031**
Random Effects			
$\tau_{00\ participant\_id}$	0.03		
$\tau_{00\ product\ category}$	0.04		
ICC	0.02		
$N_{participant\_id}$	1842		
$N_{product\ category}$	6		
Observations	11052		
Marginal R^2/Conditional R^2	0.005/0.022		

[a] Overt ordering and covert ordering are indicator variables of the experimental conditions, with the control random ordering as the reference level. In other words, covert and overt ordering are being compared to the control random ordering group. Thus, the coefficients for Overt/Covert ordering show the difference between these conditions and Control random ordering.

2.3. Procedure

The experiment involved a simulated online grocery shopping task where participants shopped for six food products for dinner for two in a simulated online supermarket environment. This task was chosen because it allowed a variety of product categories within a familiar and realistic shopping activity. Each participant was given a budget of £30 at the start of the experiment and was introduced to the task. The budget was set to be high enough that it was not possible to exceed the budget with any possible combination of product choices and participants were informed about this at the start. Participants were also informed that they could choose to enter a prize draw where 10 randomly chosen participants would get a delivery of the items that they chose plus any change from the budget. All products used in the experiment were chosen from the range available in the online grocery store of a major retailer; the picture, information and price associated with each product were obtained from the online grocery store as well.

There were six product categories: snack, soup, pizza, dessert, ice-cream, and tea. The product categories were chosen to fit the task, which was to shop for dinner for two. The choices of product categories were also subject to the constraints that there needed to be a range of products of comparable popularity and price, enough non-supermarket-own-label products in a product category, and the products within a category needed to have enough variation in terms of the carbon footprint data provided by Envirofy. Each product category was on a separate page. In the introduction screen, participants were informed about the six product categories and that they would be shown in random order. The product category pages looked like a generic online supermarket interface with products in a category listed in a single column as

[1] Given six products in each category, there are 6*5*4*3*2*1 = 720 possible orderings for a product category, and the sustainability ordering will be 1 out of the 720 possibilities. Therefore, for the majority in the control (random ordering) arm, the ordering will be different from the treatment arms. We did not exclude ex ante the possibility of randomly generating an ordering that happens to be the same as the sustainability ordering in treatment arms for the control (random ordering) arm because we want the ordering in the control (random ordering) arm to be truly random, which gives us a clear interpretation of any effects found.

[2] We chose to target online grocery shoppers (excluding participants who self-reported never having shopped for groceries online) because these were the people who would potentially be affected by the intervention, which was designed for the online supermarket environment. Recruiting using quotas plus a screening question was expected to give a sample with demographics close to the population of online grocery shoppers, which could be different from those of the general population.

the main content of the page, which mimicked the way that they would look on a mobile device.[3] An icon of the basket was shown with a number indicating the total price of the products in the basket, which was updated as the content of the basket changes. The layout of the six pages did not differ except for the product-related information. The order of the six pages was randomised for all participants independently. See Fig. 1 for a screenshot of the simulated online supermarket.

There were six products within each product category (See Online Appendix A.2 for the lists of products). Products in each category were chosen based on the following procedure: 1) products were searched using the name of the product category as a keyword in a real online supermarket environment; 2) chosen products had to differ in terms of names and descriptions from each other but be of similar sizes/weights and enough for serving two people; 3) any supermarket own-label products were avoided to make the simulated online supermarket generic.[4] A picture, a name with brief description (including size/weight), and a price was displayed for each product, as on a real online supermarket shopping page. There was a button to add the product to the basket, which would become a button to remove the product once a product was added. Only one product from each category could be added to the basket. Product choices could be changed while participants stayed on the page but could not be modified once they proceeded to the next page.

After participants completed the product choices for the six categories, they were shown the products they had chosen along with the remaining budget and were reminded about the possibility of entering the prize draw. Then they were asked to complete a questionnaire. The first question was a manipulation check, about their awareness of the intervention. Participants were asked, "In the task you just completed, how were the products on each screen ordered?" and given multiple choice from the following answers: by popularity, by price, by sustainability, by healthiness, randomly, don't know. Then participants were asked about their environmental concern, attitudes towards nudges, normative attitudes towards shopping sustainably, whether they eat meat, and demographics (age, gender, education, income) were asked (see Online Appendix A.3 for the questionnaire).

The experiment could be completed on a computer, mobile, or tablet, subject to participants' preference. During the experiment, the computer program automatically recorded the type of the device participants used to complete the experiment, the time spent on each page, and any random order generated. The company DecTech was commissioned to script and administer the online experiment.

No personnel interacted directly with the participants during the trial period as it was an online experiment. Participants in the control (random ordering) and covert ordering arm were blinded to their treatment arm. Participants in the overt ordering arm knew about the intervention but did not know what the other treatment arms were. The experiment was designed to let the participants in the overt ordering arm know about the treatment, as the research question was whether knowing about the treatment changes the treatment effect. The study data was labelled by someone other than the person conducting data analysis without revealing how participants corresponded to the treatment arms, to ensure the analyst was blinded to the treatment assignments.

2.4. Outcomes

The primary outcome of the study was a binary variable indicating whether a more sustainable product was chosen or not at the product category level. It took a value of 1 if the chosen product was one of the three most sustainable products in the category according to the Envirofy ranking, and equalled 0 if the chosen product was one of the three least sustainable products. We decided to use a binary variable as the primary outcome variable instead of the ordinal variable because using an ordinal variable as the dependent variable would require an ordinal regression model and additional assumptions would have to be made, such as the proportional odds assumptions, which might not be met. There are also greater risks of non-convergence when estimating an ordinal regression model with complicated random effects structure. (However, note that we did run ordinal regression models, treating the outcome variable as ordinal, as part of our sensitivity analysis). A cut-off had to be selected to transform the ordinal variable to binary; without a strong reason to choose a particular cut-off, we chose the middle point. The chosen primary outcome represents the likelihood of choosing the three more sustainable products in a category, which is a meaningful result to show for the interventions, as we expected a general shift towards more sustainable products.

It is also possible to use the total carbon footprint of all the six chosen products in the basket as an outcome measure, as Koutoukidis et al. (2019) did. There are two main reasons we decided not to follow this approach: Firstly, this measure would be sensitive to the carbon footprint measures of certain products and certain categories. For example, if two desserts happen to have a very big gap in terms of their carbon footprint compared to the differences between other products, the entire outcome can be driven by the choices between these two desserts. Using outcomes based on the sustainability rank instead of the actual carbon footprint number can help with this issue, making the results more generalisable. This is especially important in the sustainability case, relative to healthiness, given the controversy over how environmental impact should be calculated, and we do not want the results to be very sensitive to the numbers given by the particular sustainability measure we have chosen. Secondly, using the total carbon footprint aggregating over the different product categories would not allow us to generalise the results to other product categories. The advantage of having different/multiple product categories is that the outcome will not rely on a particular product category or the specific product categories chosen. We would be able to model how the outcome variables and the treatment effects vary across different product categories by including random effects, which enables us to estimate a treatment effect on the outcome variable generalisable to a randomly selected product category (which can be none of the six particular categories chosen in the experiment because we are using them as a "sample" of all possible

[3] Note that the layout of product lists varies across devices for real online supermarkets, usually with a single column vertical list layout like the one in this study for mobile phones, but a 4-column grid layout for wider screens. The study standardized the layout for all device types in order to get a clean effect of sustainability ordering and to maximise the power of the study given limited budget and sample size. If the layout were allowed to vary across device types, it would be difficult to interpret the results as it is not completely clear what the equivalent of top of the list position is for a grid layout, and device type would confound layout format. However, since the effect of the ordering intervention might differ depending on the layout and screen type, caution needs to be taken when generalizing the findings of this study.

[4] We chose to include six products in each product category because this study focuses on ordering of products, namely the position effects, and six products should give enough variation in terms of position of products (see Bar-Hillel (2015), Dayan and Bar-Hillel (2011) and Schmidtke et al. (2019) for research studying position effects with similar number of products in a category). Products in different positions are predicted to be chosen with different probabilities based on the assumption that individuals pay more attention to certain positions on a page. This is different from the "above-the-fold" effect, which concerns the extra effort involved in scrolling down a page. Given a fixed research budget, there is a trade-off between the number of products in each category and the number of categories. Increasing the number of product categories can help increase the power given a fixed sample size, while increasing the number in a category will not. Therefore, we settled with six products per category with six categories, given the budget available. Although there is likely to be more than six products in a broad category in an online supermarket, consumers often have a more specific idea about the item to look for than the broad category and they would search by keyword or go to a narrow category, in which case a limited number of items would show up, similar to the situation in our study.

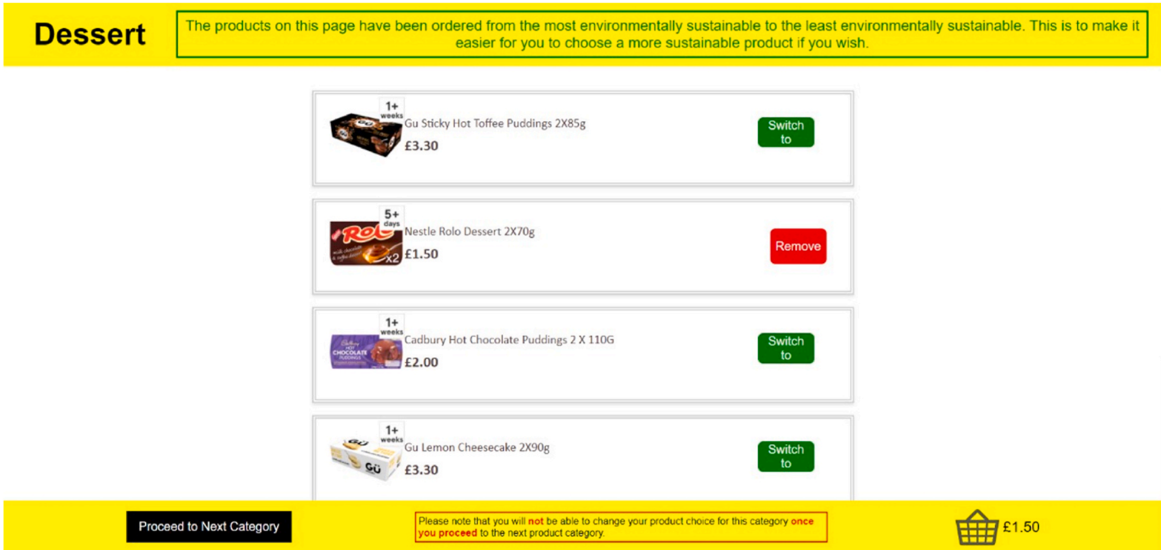

Fig. 1. Screenshot of a product category page in the simulated online supermarket for overt ordering arm, as it looked on a desktop.

product categories to estimate a distribution). When we aggregate over different product categories, the information given by the variability across different product categories is lost so we cannot model the variability across product categories and cannot estimate a treatment effect that can be generalised to a randomly selected product category.[5]

There were three secondary outcomes which are alternative forms of the primary outcome, including a binary variable of whether the participant chose the most sustainable product and an ordinal outcome variable that indicates the rank of sustainability of the product chosen in each category. These were used for sensitivity checks, which are described in Online Appendix C.

2.5. Sample size

The target sample size was 1800 participants completing the whole experiment and passing the quality checks, with around 600 participants in each experimental arm. 2100 participants were targeted to complete the experiment to allow for up to 15% to be cleaned out due to failure of quality checks.[6]

We chose our target sample size based on a power simulation, run using a logistic regression model with the primary outcome variable and random intercepts for participants and product categories, using the Bonferroni-corrected cut-off threshold $p < 0.025$ to determine whether the results were significantly different from those expected if the two null hypotheses were correct. We had a power of 0.999 to detect a difference of 8%, and a power of 0.843 to detect a difference of 5% assuming relatively low variability of individual and product category random effects (standard deviation being 0.693 and 0.203), between the covert ordering arm and control (random ordering) arm (which is in line with the range of effect sizes found in the literature). Details of power simulations, with the different scenarios considered, can be found in the OSF preregistration (https://osf.io/ehd2j) and Online Appendix B.

2.6. Data diagnostics

Participants who did not complete the whole experiment or failed the quality checks were excluded from the final sample for data analysis as described in the participants' section. There was no other post-data collection exclusion of participants. There was no missing data for any of the variables used in the data analyses.

2.7. Statistical methods

The hypotheses and analytic plan were specified before the data were collected and pre-registered on Open Science Framework (https://osf.io/ehd2j). Any data-driven analyses are clearly identified and discussed appropriately in Section 3 and Section 4.

The main model for testing the two hypotheses was a generalised linear mixed model with logistic link function given a binary primary outcome. The basic specification of the model is given in Online Appendix C. The statistical programming language R (R Core Team, 2021) and the development environment RStudio (RStudio Team, 2021) Version 2021.9.1.372 were used to perform the data analysis.

2.8. Ethics, registration and data availability

Ethics approval was obtained for this trial from LSE Research ethics committee (Ref: 57054). All participants gave informed consent before taking part in the study. This study and the data analysis plan were preregistered on Open Science Framework (https://osf.io/ehd2j) before trial launch and any data collection. The full trial protocol can also be accessed via the Open Science Framework preregistration. The data and code for the study will be made available on Open Science Framework.

3. Results

3.1. Recruitment

The online experiment was launched on the 9th of March 2022 and finished on the 21st of March 2022. A total of 5284 potential participants were assessed for eligibility; 2144 participants passed the qualification stage and started the experiment; 44 participants dropped out during the experiment; 258 participants completed the experiment but failed the quality checks, and were thus not included in the final sample; 1842 participants were included in the final sample with complete data used for statistical analyses. Fig. 2 shows the participant flow.

Baseline demographic characteristics for each arm can be found in Online Appendix Table A.2. 52.3% of the participants were female while 47.3% were male; 86.8% of the participants were white, with 6.7%

[5] The second point here also applies to an alternative outcome variable which adds up the sustainability ranks of the chosen products across all six categories.

[6] The potential rate of failing the quality checks and the number to over-recruit were determined according to past fieldwork experiences of the delivery partner.

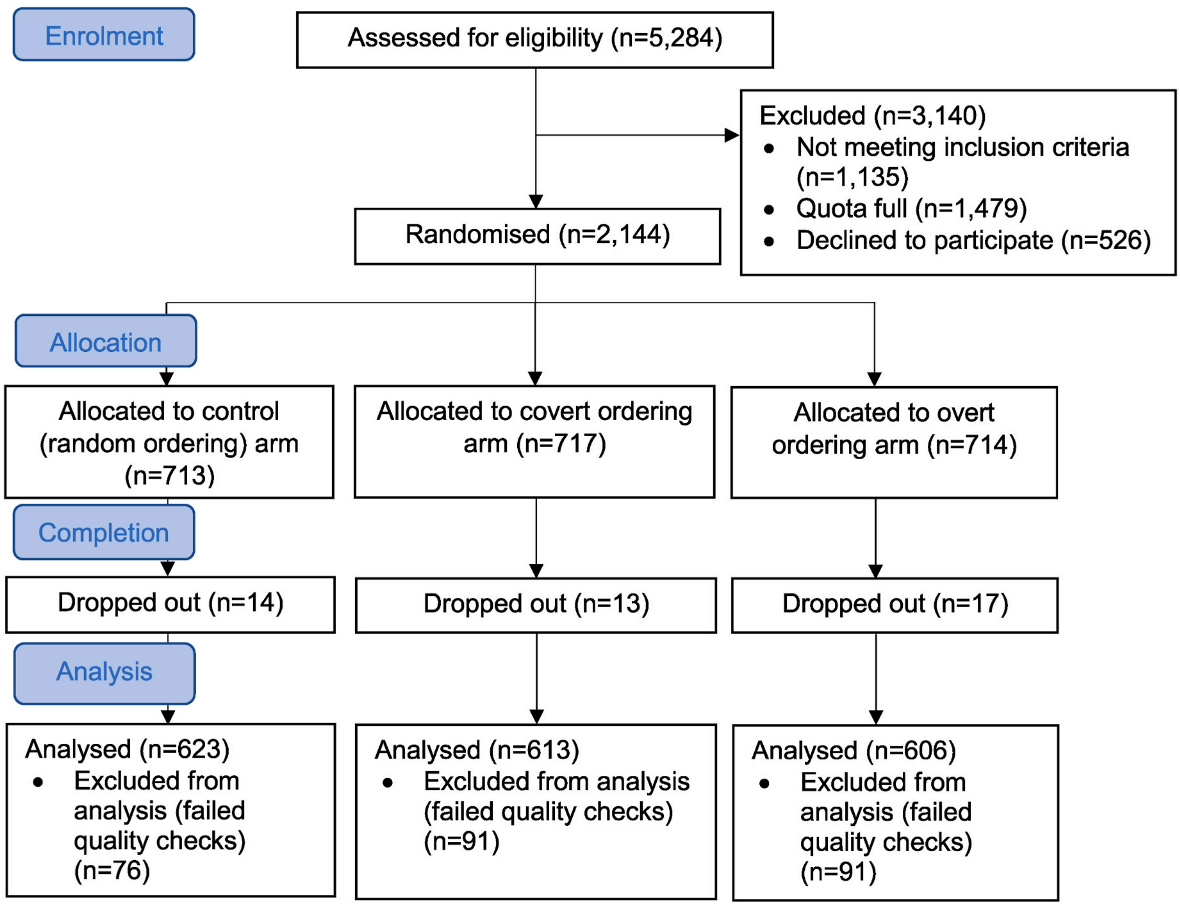

Fig. 2. Participant flow.

being Asian/Asian British and 3.2% being Black/African/Caribbean/Black British; mean age was 43.9 years (SD = 13.9); 37.2% of the participants had at least a bachelor's degree and 57.4% had total household income lower than £40,000. The modal frequency of online grocery shopping among participants was 'at least weekly' in all three arms, and 37.9% across the sample as a whole.

Participants on average spent 5.96 min on the experiment (SD = 5.62). Participants received the standard panel incentives for completing the experiment (which is confidential commercial information) and spent an average of £14.90 (SD = 1.48) on the shopping task, leaving average change of £15.10. 984 (53.4%) of participants chose to enter the prize draw. The trial was conducted according to the trial protocol without deviation.

3.2. Main results

Participants chose a more sustainable product 59.5% of the time in the random-ordering arm, 58.8% of the time in the covert ordering arm, and 59.6% of the time in the overt ordering arm, an average of 59.3% over the entire sample. Our optimal model showed that there was no statistically significant effect of the covert ordering intervention on the probability of choosing more sustainable products versus less sustainable products, compared to random ordering (OR = 0.97, 95% CI 0.88–1.07, $p = 0.533$). Furthermore, our hypothesis that the effects of the covert ordering intervention and overt ordering intervention do not differ could not be rejected (z-value = −0.533, $p = 0.594$). See Table 1 for results of the optimal model with optimal random effects structure and reduced set of covariates. The results were not sensitive to the inclusion of extra covariates.

There were demographic differences in sustainable choices. Older people were less likely to choose a more sustainable product (OR = 0.88, 95% CI 0.85–0.92, $p < 0.001$), as were people with higher education (OR = 0.91, 95% CI 0.83–0.99, $p = 0.028$), and higher household income (OR = 0.96, 95% CI 0.92–1.00, $p = 0.031$). Those who did not eat meat were more likely to choose a sustainable product (OR = 1.16, 95% CI 1.01–1.32, $p = 0.033$).

The models specified as sensitivity analyses with secondary outcomes all showed the same pattern of results (see Online Appendix C and Online Appendix D). An additional model with total carbon footprint of the six chosen products in the basket as the outcome measure found no significant treatment effects either. No statistically significant results were found for the additional analyses specified in the pre-registration (see Online Appendix C and Online Appendix D).

3.3. Exploratory analyses

Since we did not find an effect of our interventions, we performed some exploratory analyses to try to explain why we did not find an effect.[7]

We expected that the covert ordering would have an effect because automatic processes would lead consumers to choose positions that are more reachable and more salient, which we conjectured would be those at the top of a list in a digital environment. If this mechanism is at work, we would expect participants in the control (random ordering) and covert ordering arms to be more likely to select products that are

[7] The analyst was unblinded about the treatment assignment at this point as the pre-registered analysis had been completed and the extra analyses required knowledge of treatment assignment to help understand the results.

positioned at the top of the vertical list. However, in the control (random ordering) arm, products in different positions on a page were chosen by participants with similar frequencies (see Fig. 3), contradicting the assumption that people choose products in positions that are more reachable and more salient. Although in the covert and overt ordering arms, products in different positions were chosen by participants with different frequencies, the patterns varied across different product categories. Note that product positions in both the covert and overt ordering arms were determined by their sustainability ranking, meaning the same position represents the same product for these two arms. Thus, the similarity of patterns for a product category between these two arms could reflect the variance of preference for different products in a category shared by participants in both arms. A logistic regression model to predict the characteristics that make a product more likely to be chosen in the random-ordering arm confirmed that product choices are affected largely by factors other than price, weight, and position (See Online Appendix C).

We expected that the overt-ordering intervention would operate via participants noticing the ordering and consciously choosing products that are more sustainable; however, it seems that most participants did not notice. In our post-intervention questionnaire, only 19.5% of participants in the overt-ordering arm correctly answered that the products were listed in order of sustainability. The modal choice in all arms was the products were listed randomly (See Fig. 4 for the percentage of participants choosing each option to this question for each experimental arm.).

Results of extra exploratory analyses could be found in Online Appendix C and Online Appendix D.

4. Discussion

We found that listing the products in an online supermarket in order of sustainability did not have an effect on the proportion of sustainable choices, either when the ordering was covert or when it was accompanied by a statement informing participants about the product ordering. Participants chose a more sustainable product 59.5% of the time in the random-ordering arm, 58.8% of the time in the covert ordering arm, and 59.6% of the time in the overt-ordering arm. Nor did we find any effect of the interventions in sensitivity analyses on secondary measures, which included the selection of the most sustainable product in a category and the sustainability rank of chosen products. This may be because neither of the two mechanisms by which we surmised our interventions would work were operative. We expected that the covert ordering would work because there would be an effect of position, with participants choosing products that were higher in the lists because they were more reachable and salient. However, additional analyses suggested that, in the random-ordering arm, there was no effect of the position of a product on the product category page. We expected that overt ordering would operate via conscious decision-making processes. However, in the overt-ordering arm, only 19.5% of participants correctly identified that the products were ordered by sustainability in a post-task questionnaire, so it seems the majority did not notice the statement telling them about the ordering.

It is surprising that our covert ordering intervention did not have an effect, given results from other studies that carried out similar interventions. Our study was powered to detect a 5% difference, which is the magnitude of the difference found by Koutoukidis et al. (2019). Our study does differ from many of the few existing studies, which were based on behaviour in bricks-and-mortar environment using hard-copy menus when healthier items were placed at the top of lists (Dayan &

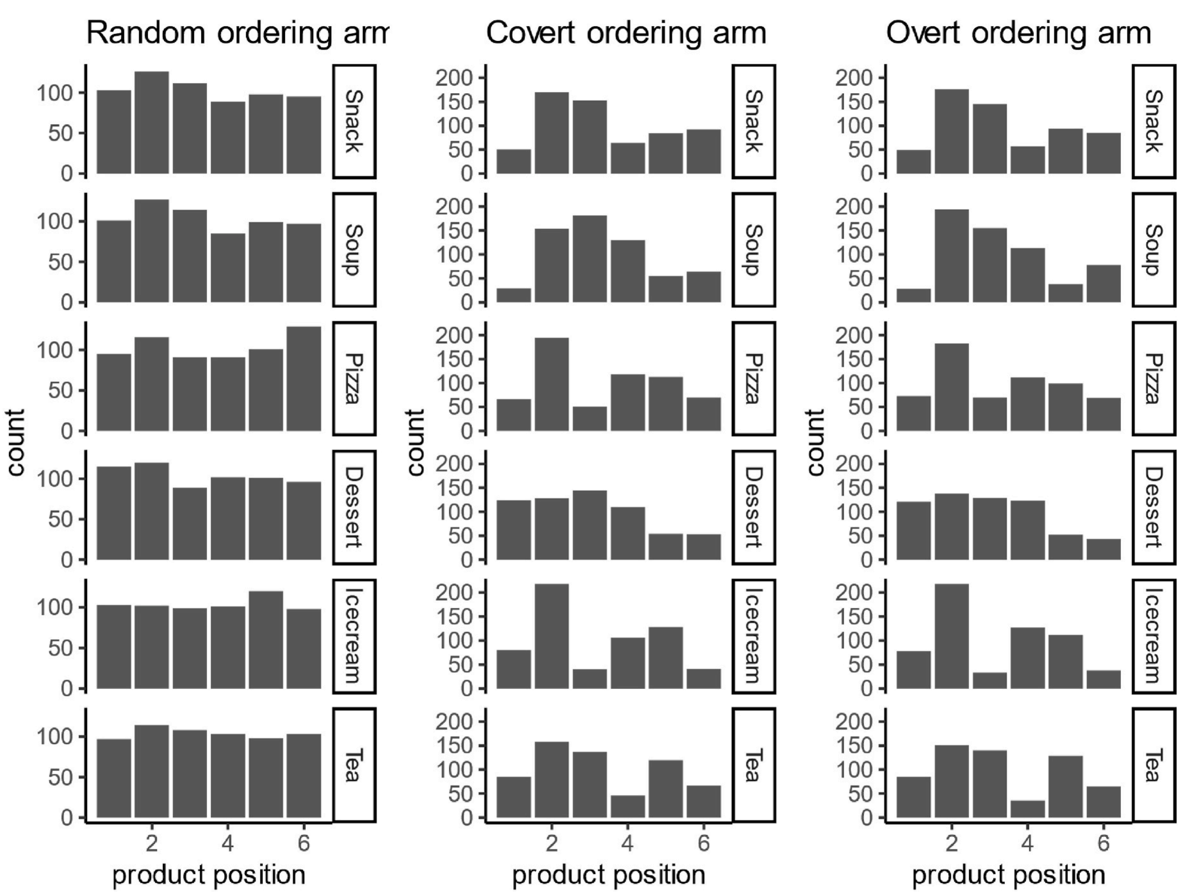

Fig. 3. Frequency of choices by product position.

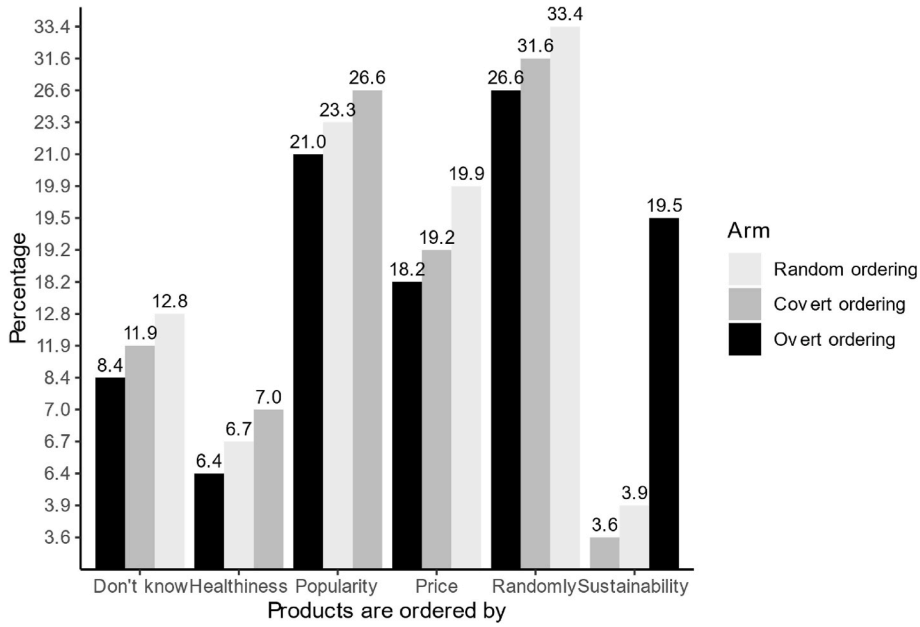

Fig. 4. Percentage of participants choosing each option of product ordering by experimental arm.

Bar-Hillel, 2011; Mueller et al., 2020), including the one that ordered products by environmental impact (Langen et al., 2022). There are also differences in study design, for example we used a randomised controlled trial, whereas Schmidtke et al. (2019) used a pre-post design in actual kiosks. In comparison, participants in our study made product choices in a simplified online supermarket environment following a structured shopping task. This setting might make it easier for participants to explore and pay attention to all product options, compared to a noisier off-line environment or an online environment with more choices. However, it should also be noted that our modelling approach minimised Type-I errors and studies that used traditional approaches such as the Analysis of Variance have a higher risk of finding spurious effects (Jaeger, 2008). We used logistic mixed-effects models, which included separate error terms for participant and product category, allowing us to incorporate additional uncertainty in the estimates of intervention effects associated with variation between participants and categories. Models that do not take this variation into account are likely to underestimate the standard errors of coefficients, potentially leading to an overstatement of statistical significance.

Another possibility is that ordering interventions only have an effect in online interventions when there is the potential for a lot of scrolling, so people do not make it to the bottom of the list. In our experiment, the number of products that were shown on the screen without scrolling varied by device model and screen size, but it was designed so that four products were shown without scrolling on most devices and screens. As mentioned in Footnote 4, we conjecture ordering to have an effect based on position, which is different from scrolling, which relates more to the "above-the-fold" effect. If scrolling modified the effects, we would expect products displayed at the bottom two positions to be selected less as participants would need to scroll down to see them; however, there is no evidence of this in our data (see Fig. 3 and Online Appendix Table A.7). We cannot rule out the possibility that if there were more products and more scrolling was required to see products at the bottom of the list, then products further down the list might be chosen less. However, in that case, it is questionable whether ordering is still the relevant mechanism (when one thinks of ordering as being analogous to placing products at the top of the list on a physical menu). Instead, one might think it is more similar to interventions that decrease the availability of certain products or increase their costs, by making them harder to find.

As far as we know, ours is the first study to investigate ordering effects for sustainable products in online environments; the closest comparator study aims to promote the choice of healthier products. Koutoukidis et al. (2019) also used a simulated online supermarket environment. The task was slightly different, as participants were given a 10-item shopping list and could browse categories rather than going through a forced-journey; and it was entirely hypothetical, participants did not receive the products they chose. The primary outcome measure was the saturated fat content of the whole basket, which decreased by 5%. One of the secondary outcome measures showed that there was a 10% decrease in the percentage of products with less than 1.5% saturated fat per 100g in the basket, i.e. products that can be labelled as 'low' in saturated fat content according to Department of Health guidance (Department of Health and Social Care, 2016). So on average participants put one more product that was low saturated fat in their baskets. Some products that are low in saturated fat are obviously labelled as low fat, for instance semi-skimmed milk or lighter butter (both of which were used in the experiment). Open-ended comments left at the end of the experiment suggested that participants wanted to buy healthier food and that they noticed that the healthier products were at the top of the ordering. This is potentially quite different from sustainable products, where it is not always obvious which product is more sustainable, especially within product categories, and where consumers often do not know what choices will reduce their carbon footprints (Kause et al., 2019). Further, when making food choices, health and nutrition are more important to consumers than sustainability (Fox et al., 2021; Ghvanidze et al., 2017; Grunert et al., 2014). So it is possible that re-ordering according to nutrition content is noticed by consumers and supports their reflective decision-making, in a manner that re-ordering according to sustainability did not.

Even in our overt ordering intervention, where we had a statement at the top of the product category telling participants about the ordering, participants did not notice that products were listed in order of sustainability. Other researchers have also reported that many people did not notice their disclosure statements (see Wachner et al. (2020) for an online study and Kroese et al. (2016) for a field study). We had thought that putting the statement in a box at the top of the page would be salient, but participants may have focused on the product list itself. Our interface was simplified compared to an actual online supermarket, so in real-life shopping people might be even less likely to pay attention to information about sustainability rankings of products. Future research could investigate how to make an environmental ordering more salient. One possibility would be to use pop-ups, which have been successful in prompting people to make healthier swaps (Bunten et al., 2021; Huang et al., 2006; Jansen et al., 2021; Koutoukidis et al., 2019); however see Forwood et al. (2015) for a swap experiment in a simulated supermarket that was not successful. However, it should be noted that a trial using pop-ups in a real online supermarket, where students were given money to place an order and actually received their products, pop-ups for healthy choices did not increase the proportion of healthy purchases despite being powered to detect a difference of 1% (Stuber et al., 2022). More field research in real supermarket environments is required to establish the external validity of the effects of pop-ups on behaviour, but they at least seem to be noticed in simulated environments.

The trial in this study was designed to simulate an online supermarket environment in real life, and to be as close as possible to a real online supermarket. The experimental interface was designed to mimic the layout of existing major online supermarkets and all the products with their names, prices and pictures were taken from existing online supermarkets as well. A large sample from England, Wales and Northern Ireland representative of age, sex and ethnicity was recruited to complete the experiment, with real material incentives in terms of getting the chosen products and strict quality checks to ensure that final sample excluded participants were likely to have not participated fully. Therefore, the absence of position effects and the large variation in preferences for different products should reflect to some extent consumer behaviour in real-life online grocery shopping environment. Even for products in a relatively narrow product category that were chosen to be comparable to each other, characteristics other than position and price play important roles in determining the purchasing decisions. Research has pointed out the importance of habits and taste in food choices (Fox et al., 2021; Osman & Jenkins, 2021; Riet et al., 2011); our results show that such habits might be too ingrained to be changed by subtle modification of situational cues, and more explicit interventions such as giving consumers carbon targets for their baskets as done in Kanay et al. (2021) might be needed.

There are limitations to this study. As mentioned, given the reported variance estimates, our trial was able to detect an effect of 5%. It is possible that the effects of ordering interventions are smaller than 5% so cannot be detected by the current sample size. However, the point-based estimates of our optimal model did not suggest there are such effects. Secondly, it is possible that our results are specific to the products chosen, the product categories chosen, the number of products on each page, the measure of sustainability, and other details in terms of experimental design. We did try to choose products that were comparable to each other in terms of popularity and price, while still having variance in their carbon footprint. Nevertheless, we cannot rule out the possibility that the findings are specific to the experimental design and more research using variations of the design is welcomed to generate more evidence on the effects of such interventions. Finally, despite our effort to simulate the online grocery shopping experience with high ecological validity and recruit a sample that is representative, the results still come from an online experiment completed by panellists, which potentially threatens the ability to generalise from our results to the real-life situation we are studying (external validity) and which could be better dealt with using a field trial.

It is worth pointing out that, the trial simplified many of the real-life considerations. In a real online supermarket, consumers can go straight to the lists of their favourite products or products they have bought before and choose from there, without being exposed at all to other products that might be more sustainable (Bunten et al., 2022). Consumers can also sort the products by price, popularity, or other factors that they care more about, which is likely to overwrite any default ordering that is intended to nudge consumer choices. Because our online shopping task did not have either of those features, we increased the chance that we would find an ordering effect compared to a real-life environment, and we still did not find an effect.

Many interventions around changing the choice architecture have been shown to be effective in encourage healthier and more sustainable diets. However, the particular interventions investigated in this study – ordering food products in a simulated online supermarket by their environmental impact covertly/overtly – were not found to generate the expected increase in consumers' likelihood of choosing more sustainable products. Our results suggest there are ingrained preferences for different grocery products that largely determine purchasing choices, and the difficulty of conveying information effectively to consumers in the online grocery shopping environment. To our knowledge, this study is the first to explore the effects of ordering interventions by environmental impact in an online shopping environment. More research needs to be done to continue to fill the evidence gap, provide more solid answers to the research questions on the effectiveness of such interventions, and enrich our understanding of when changing choice architecture works.

Author contributions

Shi Zhuo contributed to study design, data collection, analysis and writing of the paper; Michael Ratajczak contributed to study design, data collection, analysis and writing of the paper; Katie Thornton contributed to study design and writing of the paper; Phil Jones contributed to study design and writing of the paper; Ayla Ibrahimi Jarchlo contributed to study design, data collection and writing of the paper; Natalie Gold contributed to study design, data collection, analysis and writing of the paper. All authors have approved the final article.

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Declaration of interest statement

There is no financial/personal interest or belief that could affect the objectivity of all authors in this study.

Ethical statement

Ethics approval was obtained for this trial from LSE Research ethics committee (Ref: 57054). All participants gave informed consent before taking part in the study. This study and the data analysis plan were preregistered on Open Science Framework (https://osf.io/ehd2j) before trial launch and any data collection. The full trial protocol can also be accessed via the Open Science Framework preregistration. The data and code for the study will be made available on Open Science Framework.

Declaration of competing interest

None.

Data availability

Data will be made available on Open Science Framework

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.appet.2022.106368.

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