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# Nudging, fast and slow: Experimental evidence from food choices under time pressure

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**Abstract**

This paper explores the relationship between decision-making speed and the effectiveness of two nudges – carbon footprint labelling and menu repositioning – aimed at encouraging climate-friendly food choices. Building on Kahneman's dual-process theory of decision-making, we examine whether these interventions are more effective in fast, intuitive (System 1) contexts compared to reflective, deliberate (System 2) ones. Using an incentivized online randomized controlled trial with a quasi-representative sample of British consumers (N=3,052) ordering meals through an experimental food-delivery platform, we introduced a time-pressure mechanism to capture both fast and slow decision-making processes. Our findings suggest that menu repositioning is an effective tool for promoting climate-friendly choices when decisions are made quickly, though the effect fades with extended deliberation. Carbon labels, in contrast, showed minimal impact overall but reduced emissions among highly educated, climate-conscious individuals under time pressure. The results imply that choice architects should apply both interventions in contexts where consumers make rapid decisions, such as digital platforms, to help mitigate climate externalities.

**Keywords:** carbon-footprint labelling, choice architecture, food-delivery apps, low-carbon diets, dual-process models, system 1

**Competing Interests:** The authors declare no competing interests.

**JEL Codes:** C90, D04, I18, D90, Q18, Q50

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# 1 Introduction

In Thinking, Fast and Slow, Daniel Kahneman (2011) puts forth the dual-process theory of choice, which posits that the human mind has two different "cognitive systems": one cognitive process is fast and intuitive (System 1), and one is slow and analytical (System 2). System 1 is quick; most of the time it runs on auto pilot. Emotions often kick in. It enables fast decisions but leaves individuals more susceptible to cognitive biases, such as primacy and order effects (Rey et al., 2020; Tversky & Kahneman, 1974). System 2, in contrast, is slow. It encourages careful, deliberate reasoning and reflection, thereby demanding more time, cognitive effort and self-control. System 2 is harder to manipulate. Though scientifically well-supported, such a dual-process theory is itself a heuristic, a simplification of the complex processes of human decision-making.

Marketers have sought to exploit these different decision-making styles for decades, and in recent years there has been a growing interest in the use of nudging, i.e., changing the choice architecture of a decision without changing monetary incentives or the regulatory frame, to correct for potential biases and help people make better, welfare-enhancing decisions (Sunstein, 2020; Thaler & Sunstein, 2008). Even more recently, externality-addressing 'green nudges' have been developed that seek to steer consumers towards more sustainable behaviours through engaging their System 1 thinking (Carlsson et al., 2021).

In the domain of food consumption, carbon footprint labelling and menu repositioning are two popular interventions proposed to encourage more climate-friendly food choices, mostly by avoiding ruminant meat (Ammann et al., 2023; Lohmann, Pizzo, et al., 2024; Reisch, Sunstein, Andor, et al., 2021). Menu repositioning moves low-carbon dishes to the top of the menu, making them easier to choose and creating an anchoring effect such that choices further down the menu will be compared to those at the top. Carbon footprint labels use traffic-light colour schemes to make low-carbon food choices more salient and simple, providing a visual warning against high-carbon meals through colour cues (Reisch, Sunstein, & Kaiser, 2021).[1] While repositioning has consistently been found effective in encouraging more sustainable choices (Gravert & Kurz, 2021; Jostock et al., 2024; Lohmann, Gsottbauer, et al., 2024), the evidence on carbon labels is mixed (Beyer et al., 2024; Lohmann, Gsottbauer, et al., 2024; Maier & Fesenfeld, 2024; Muller et al., 2019). Given that a majority of nudges are designed to affect System 1 decisions – described as "architectural nudges" (Reisch & Sunstein, 2021) or "pure nudges" (Carlsson et al., 2021) – it is surprising how little work has been done to learn whether these nudges are effective only in fast decisions, or if they can also affect slower System 2 decision-making.

If nudges mostly affect fast System 1 decisions, this can help explain differences in the effectiveness of nudges across studies, settings and domains. For example, changing the menu order in a busy lunch restaurant might have a much stronger effect on choices than the same changes of item positioning on the menu at a relaxed diner. Ordering take-out in an app on the way home from work might also lead to different choices compared to leisurely browsing on a Sunday night on the couch (e.g., Jesse et al., 2021). Some studies have aimed to measure the effect of nudges under varying levels of cognitive

[1] Some carbon labels also provide detailed information about the product and its carbon emissions. In those cases, carbon labels can be understood as information provision and would mostly affect System 2 through a deliberate decision process.

load (Altmann et al., 2022; Bruns, 2019), yet the evidence on decision-making speed has mostly been anecdotal or endogenous to the decision maker's speed (Lohmann, Gsottbauer, et al., 2024).

In this paper, we present experimental evidence for fast and slow decision-making within two popular behaviourally informed interventions aimed at promoting climate-friendly food choices. We conducted an incentive-compatible online randomized controlled trial with a representative sample of UK consumers (N=3,052) in which participants ordered dinner through an experimental food-delivery platform. Modelled after popular real-world food-delivery apps, the experimental platform offered a selection of restaurants with a variety of meal options to replicate an authentic consumer choice environment. Importantly, choices were incentivized through a random incentive mechanism offering a one in 30 chance to actually receive one's meal choice. Participants were randomly assigned to a control group or one of two intervention conditions: (1) a menu-repositioning nudge that placed low-carbon meals at the top of the menu, and (2) a traffic-light coloured carbon footprint label that provided environmental-impact information for each meal. To observe both fast (intuitive) and slow (reflective) decision-making for each individual, we put respondents under time pressure, utilizing a continuous time-pressure choice-process elicitation mechanism (Crosetto & Gaudeul, 2023). They were given 90 seconds to choose a meal on the platform and were incentivised to make an initial rapid choice (by the 10-second mark), with the option to subsequently revise their choice within the allotted total timeframe. This design captured each participant's perceived optimal meal choice at any moment and tracked all choice revisions, enabling us to observe when and how decisions shifted over time. We hypothesized that in a choice setting with little time where food choices are fast and intuitive, both carbon labelling and menu repositioning would increase climate-friendly choices compared to presenting choices in random order and without carbon labels. However, in choice situations with enough time to engage System 2, we expected these effects to decline.

Results showed that menu-item repositioning is an effective strategy for promoting climate-friendlier choices when individuals make fast choices, yet this influence is short-lived, and the climate impact of choices made under this nudging intervention converges with that of the control group once people are given sufficient time to revise their choices. This finding implies that menu repositioning is most likely to achieve its aim in situations where people spend little time deliberating about their food choices, and rapid, intuitive (System 1) decision-processes dominate. In contrast, carbon footprint labels were unable to achieve a reduction in emissions of food choices, on average, both under time pressure and after people had sufficient time to reflect on their selection. But for the group of highly educated and climate-conscious consumers, the labels did lower meal emissions under time pressure, suggesting that for this group, they are an effective nudge.

Our paper relates to several strands of the behavioural and environmental economics literatures. First, there is a large literature in economics and psychology studying dual-system theories (Kahneman, 2011). A substantial body of research utilizes the framework of fast versus slow decision-making to explore how timing influences a range of economic choices including risk and social preferences. To do so, most studies manipulate decision time to encourage either fast, intuitive choices or slower, more deliberative ones (e.g., Kocher & Sutter, 2006; Rand et al., 2012). Overall, evidence remains mixed (see meta-analyses by, e.g., Capraro, 2024; Rand, 2016). Surprisingly little research has examined the link between cognitive biases and choices under time pressure. For instance, Crosetto and Gaudeul (2023) find that context effects such as the 'attraction effect' decline over time. Our study connects to the broader literature on context effects, which demonstrates that contextual factors can influence diverse outcomes including voting and financial and consumption choices (e.g., Berger et al., 2008). Order effects, a key context effect, occur when the sequence in which options are presented influences decision-making. There is broad evidence that they impact various settings, including ballot order in elections (Miller & Krosnick, 1998), job ad sequence on employment choices (Ajzenman et al., 2021), menu item order on meal choice (Gravert & Kurz, 2021) and screen placement on product clicks in online marketplaces (Ghose et al., 2014).

Second, our paper contributes to the fast-growing experimental literature on interventions to promote more sustainable dietary choices.[2] Carbon footprint labels have been evaluated in a range of field settings, including supermarkets (Bilén, 2022; Elofsson et al., 2016; Maier & Fesenfeld, 2024), university canteens (Beyer et al., 2024; Brunner et al., 2018; Lohmann et al., 2022; Schulze Tilling, 2023) and restaurants (Casati et al., 2023), and the results suggest that labels are able to achieve modest increases in climate-friendly choices. Some studies found no overall impact of labels (Lohmann et al., 2022; Maier & Fesenfeld, 2024); and several other studies have shown that choice-architecture interventions, specifically menu-item repositioning, can be effective in promoting lower-carbon food choices (Gravert & Kurz, 2021; Lohmann, Gsottbauer, et al., 2024).

Third, our paper adds to the literature on the generalisability, scalability, and transferability of behavioural interventions across different domains and settings (Al-Ubaydli et al., 2021). Szaszi et al. (2018) argue that we need a much better understanding of when and why nudges work to design nudges that consistently and reliably change behaviour. Similarly, Lohmann, Pizzo, et al. (2024) highlight in their meta-analysis of food policy interventions the importance of systematically addressing unexplained heterogeneity in effect sizes to unlock the full potential of such policies. Saccardo et al. (2023) analyse data from 123 randomized controlled trials, finding that the efficacy of nudges depends on factors such as baseline uptake, time horizon, and breadth of outcomes. Improving our knowledge about the circumstances under which nudges work will help foster realistic expectations about their impact and support the development of welfare-enhancing interventions (Allcott et al., 2022; Bryan et al., 2021; DellaVigna & Linos, 2022). Our findings offer new insights into how time pressure influences the effectiveness of two prevalent nudges.

Overall, this paper – like many others before it – reflects the immense impact that Kahneman's seminal work on cognitive systems had (and is still having) in social science decision-making research. Our findings also highlight practical implications for demand-side climate policies aiming to steer consumers

[2]This rapidly expanding body of literature has examined various approaches, including manipulating the availability of options (Garnett et al., 2019; Klatt & Schulze Tilling, 2024; Lambrecht et al., 2023; Merk et al., 2024), education and information-based interventions (Fosgaard et al., 2024; Imai et al., 2022; Jalil et al., 2023; Perino & Schwirplies, 2022; Pizzo et al., 2024), fiscal interventions and other financial incentives (Faccioli et al., 2022; Lohmann, Gsottbauer, et al., 2024; Panzone et al., 2018) and a range of nudge-type strategies (Banerjee et al., 2023; Dannenberg & Weingärtner, 2023; Dannenberg et al., 2024; Kurz, 2018; Panzone et al., 2021, 2024). For a comprehensive overview of effect sizes across intervention categories, see the systematic review and meta-analysis by Lohmann, Pizzo, et al. (2024).

towards more climate-friendly food choices.

# 2 Methods and data

## 2.1 Experimental set-up

In September 2024 we conducted an incentive-compatible online randomized controlled trial using a simulated food-delivery app[3] with a nationally representative sample of 3,052 adults in the UK. Participants were tasked with ordering a meal on our app and completed brief pre- and post-intervention surveys. The experiment was pre-registered via AEA Trial Registry[4] and received ethical approval through the Cambridge Judge Business School Ethics Review Group.

Participants first completed a brief pre-intervention survey to capture food-consumption habits and preferences, experience with delivery platforms and their political identity. Prior to the food-choice task, they had to pass an attention check[5] and were subsequently given detailed instructions about the task and the mechanism used to determine payoff-relevant choices (see Appendix A3 and A4 for details).

The simulated food-delivery platform consisted of nine restaurants, closely based on real-world equivalents, offering a range of popular cuisines representative of the UK food-delivery landscape. Restaurant menus were limited to main meal bundles, providing a complete and substantial meal (e.g., burger with fries, or curry with rice), and prices were adjusted to match market prices from July 2024 for a realistic experience. Participants could choose from a total of 87 unique meals, for which carbon footprint and corresponding impact scores were calculated.[6] Appendix Figure A2 displays the distribution of available meals across five climate-impact categories (A–E).

All choices on the platform were incentivised using a random incentive mechanism whereby a subset of participants received one of the meals they selected on the app within a £20 budget. The remaining balance was transferred directly to the participants' bank accounts. Afterwards, a post-intervention survey was conducted to measure the factors influencing participants' choices and to assess their satisfaction, attention to the interventions, and other attitudes and preferences. This included attitudes towards climate change and food variety that may have overly primed participants in the pre-intervention survey.

[3]The platform "Take a BITe" was developed by the Behavioural Insights Team (BIT) and has been employed in prior research (Bianchi et al., 2023; Lohmann, Gsottbauer, et al., 2024).

[4]AEARCTR-0014349: https://doi.org/10.1257/rct.14349-1.0

[5]Participants who failed the attention check once were allowed to revise their responses and finish the study. However, those who failed the attention check twice were not permitted to continue with the experiment.

[6]As recipes for meals of major restaurant franchises are not publicly available, simplified recipes consisting of the most important (main) ingredients were developed in collaboration with Foodsteps for the purpose of this study. Carbon footprint information, impact ratings (ranging from low to high) and labels were provided by the Foodsteps platform.

## 2.2 Experimental Groups

We randomly and equally allocated participants (N=3,052) to different versions of the food-delivery platform across three experimental groups using a simple randomisation procedure: First, the control group used a version of the platform without any interventions, and menus were displayed in random order. Second, in the carbon label group, participants were shown a carbon footprint label on each menu item, indicating a low to high environmental impact. The order of restaurants and menu items was randomly presented. The third group, the menu repositioning group, was shown a platform where restaurants and menu items were re-arranged based on their climate impact. Restaurant and item rankings (within restaurants) were determined based on the GHG intensity (kg $CO_2$e / kg) of each meal and thus align with the carbon footprint labels.

The label and its life-cycle calculations were developed in collaboration with our industry partner Foodsteps.[7] The label was pre-tested with a sample of 150 participants from the UK, recruited via Prolific in August 2024 (see Appendix A5). Three alternative label designs were evaluated, with participants rating them on various criteria, including the quality of information provided, clarity, conciseness, comprehensibility, trustworthiness, visual appeal and suitability for food-delivery apps. Participants each evaluated one label design under time pressure (30 seconds) and the remaining two with unlimited time. The label with the highest overall score under time pressure was subsequently used in the main experiment. The selected design features a descriptive, traffic-light coloured, 5-point scale ranging from A (very low) to E (very high). Impact scores (A–E) were based on the Greenhouse Gas (GHG) emissions intensity (kg $CO_2$e / kg) of a given meal, calculated based on the meal's individual ingredients. Impact score cut-offs were determined by the Global Carbon Budget for Food (2019 EAT-Lancet Commission), whereby only products aligning with the Paris Agreement targets are given an A rating.

Figure 1 illustrates the food-delivery app interface and decision environment encountered by participants during the experiment. Panel A displays the carbon-labelling condition, and Panel B the menu-repositioning condition. From left to right, participants first selected from nine restaurant options, which led to the display of the respective restaurant's menu. After they chose an item, a pop-up window appeared, providing key details (item name, price, description, dietary information, and carbon labels) and allowing participants to add the item to their basket. Although participants could view their basket throughout the process, they were automatically checked out at the end of the 90-second decision period, with no option to check out manually.

## 2.3 Elicitation of meal choices and time-pressure mechanism

After completing a brief pre-intervention survey, participants received detailed instructions about the meal-choice task, which was framed as ordering dinner (one meal) for themselves through a food-delivery app. Each participant was given a virtual budget of £20 to spend on the app, with a one in 30 chance of receiving their order delivered to their home at a preferred date and time. Participants were also

[7] See https://www.foodsteps.earth/

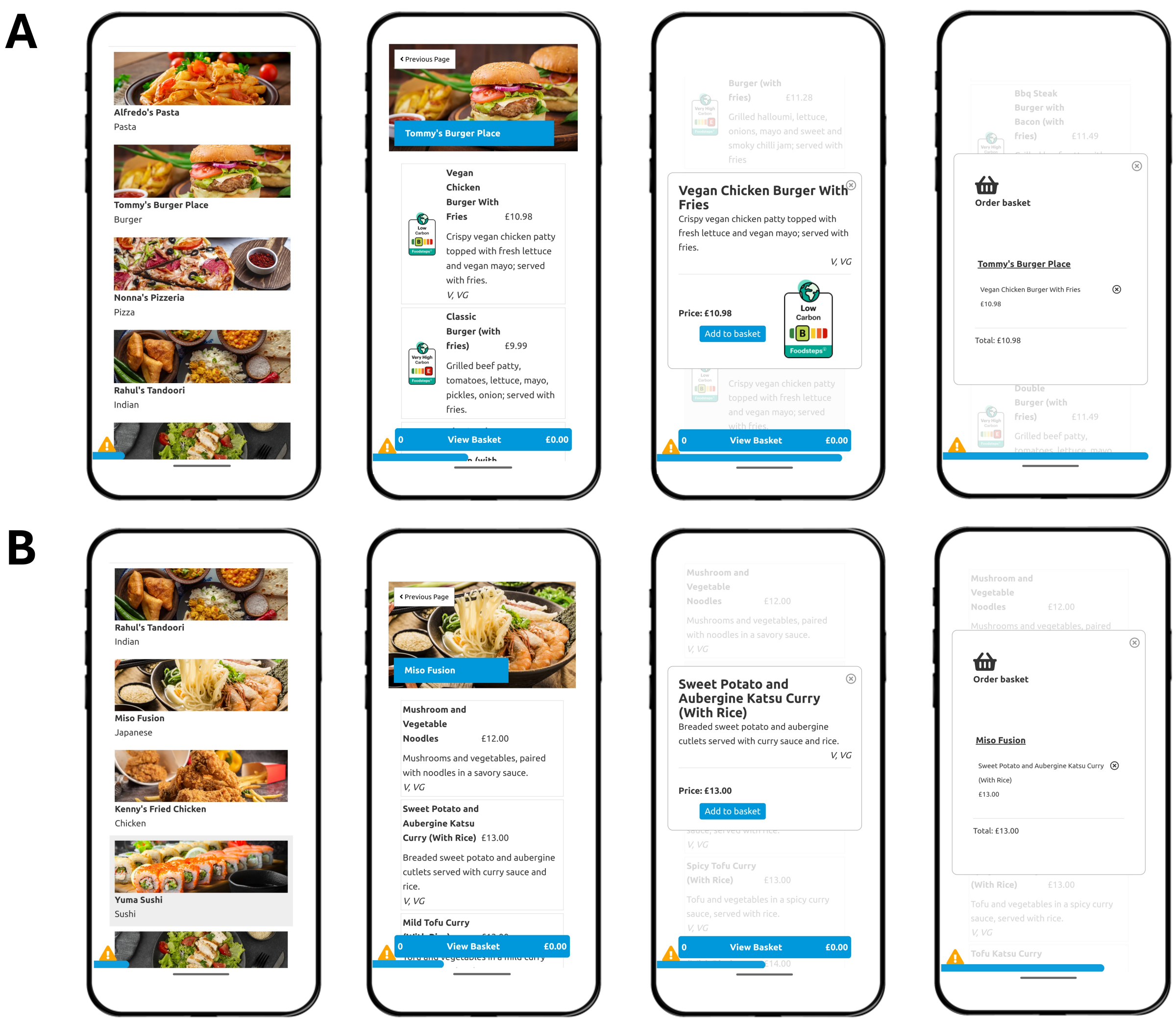


**Figure 1:** Illustration of the choice environment within the food-delivery app for the carbon-labelling condition (Panel A) and the menu-repositioning condition (Panel B)

informed that any remaining balance would be paid out via bank transfer. They were encouraged to use the food-delivery app as they normally would, allowing them to browse multiple restaurants, view the respective menus, and add or remove items from their shopping basket.

Participants were then familiarized with the time-choice elicitation mechanism, adapted from Crosetto and Gaudeul (2023) and originally proposed by Caplin et al. (2011). This mechanism induces continuous time pressure using an ex-post random stopping mechanism, thus encouraging participants to make a first rapid meal choice but allowing for subsequent choice revisions. Unlike alternative commonly used time-pressure mechanisms, such as randomly assigning participants to different time lengths, this approach allows us to observe 'fast' and 'slow' choices and causally investigate the effects of time on participants' meal choices.

Participants were informed that they had 90 seconds to add meals to their shopping basket and were able to make as many choice revisions as they wanted. Any new item added to the basket automatically replaced the current choice if a previous selection had been made. Participants were unable to manually check out before 90 seconds, yet all their choices over the time period were saved. A progress bar at the bottom of the screen indicated the remaining time. After 90 seconds, participants were automatically checked out and proceeded to the post-intervention survey.

This mechanism imposed acute time pressure through a random stopping rule, where a second – between 10 and 90 – was randomly selected after completion of the choice task to determine the meal that participants would ultimately receive if they were selected as a winner. If their basket was empty at that second, no meal was ordered, and no payout was made. Participants were thus incentivized to make a fast, potentially provisional choice, with the option to revise their choices during the remaining time. Ten seconds was chosen as the lower bound to allow for meaningful first choices, and to avoid choices that were neither reflective nor influenced by context effects. Figure 2 illustrates a possible choice pattern and three alternative scenarios.

In this example, Meal A was chosen at 32 seconds, Meal C at 46 seconds and Meal B at 70 seconds. In Panel A, the randomly drawn second is 39, and the payoff-relevant meal is thus Meal A. In Panel B, the randomly drawn second is 78, indicating that Meal B would be the ordered meal. Finally, in Panel C, the randomly drawn second is 18, at which no choice had been made (i.e., the basket was empty), resulting in no payout or meal delivery if this participant were to be declared a winner.

Participants were clearly instructed about the time-pressure mechanism and had to complete a series of comprehension-check questions prior to starting the food-choice task (see Appendix A3 for details). The average number of correct responses was 4.3 (out of 7), indicating that the majority of respondents understood the time-pressure mechanism. If questions were answered incorrectly, the correct answers were shown to participants before they could proceed. While we cannot ensure that all participants fully understood the mechanism, it is unlikely that such misunderstandings substantially influenced the results.

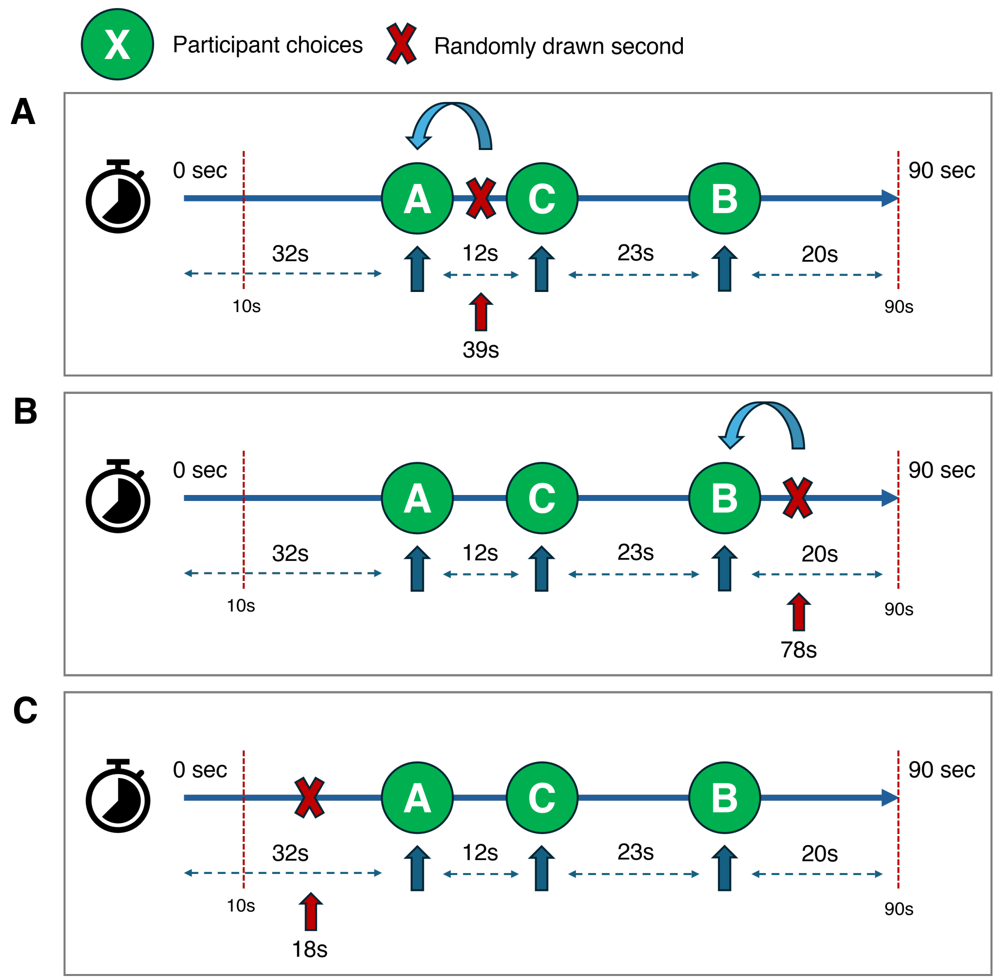


**Figure 2:** Illustration of the time-pressure mechanism with three examples: randomly drawn second at 39s (Panel A), 78s (Panel B) and 18s (Panel C).

## 2.4 Incentivisation

Participants were given a virtual budget of £20 to spend on their online food order, allowing them to select any meal available on the platform. The average meal price was £11.72, with the most expensive option priced at £16.50. Choices were made incentive-compatible using a random incentive mechanism: One in 30 participants (3.3%) was randomly selected to receive their meal order (or the closest possible match) after completion of the experiment. In a companion survey, winners were subsequently asked to choose a date and time (from a selection of dates) on which they would like to receive their meal. Meal orders were then placed by the research team using Deliveroo. Any remaining budget was paid out to participants via an online transfer. Alternatively, winners were given the option to donate the value of their meal to a UK-based food bank.[8]

[8]Incentivisation summary statistics are provided in Appendix Table A5. Due to a large proportion of rural and suburban participants, a subset of deliveries were not possible due to unavailability of delivery services. Affected participants were compensated accordingly.

## 2.5 Data and key outcomes

The data collected from every participant consist of a record of all the meal choices added to their basket during the 90-second time window of the food-choice task. From this data, we identify several food-choice outcomes. Specifically, we assess the carbon footprint (GHG emissions intensity measured in kg $CO_2e$ / kg) of their meal order, whether they opted for a meal with a high carbon impact (classified as an impact score of D or E), and if they selected a meat-based main meal. We differentiate between initial choices (first choices) and any subsequent changes (all other choices).

We also set three cut-off points to look at how participants make decisions in different time windows. We use the 15- and 30-second thresholds for fast-decision measurements based on prior observations indicating that approximately 80% of choices are made under 30 seconds. This pre-registered threshold of 30 seconds is supported by previous experiments on the delivery platform (Lohmann et al., 2024). Since we are interested in capturing intuitive decisions, we also assess choices at 15 seconds, which represents very rapid decision-making. It also closely aligns with the median first choice (at 17 seconds). While these thresholds involve some judgement, our results demonstrate that findings remain consistent regardless of these cutoffs, reinforcing their suitability for measuring 'fast' decisions. 'Slow' decisions are assessed at the full 90 seconds.

In addition to the key outcomes, we collected socio-demographic information (e.g., gender, age, location, income, education) and other relevant variables including dietary preferences, meal-delivery habits, attitudes towards climate change and choice decision factors.

## 2.6 Sample characteristics

The experiment included 3,052 participants recruited via an online survey panel (Predictiv) developed by the Behavioural Insights Team.[9] The sample is quasi-representative of the UK population that frequently orders food online. Furthermore, it aligns with the general UK population in terms of age, gender, and education. Table 1 presents the socio-demographic characteristics of the sample, which consists of 51% female participants with an average age of 40.5 years. Most participants (84%) live in urban or suburban areas, and 32% have higher education. Politically, participants are 31% left-leaning, 46% neutral and 23% right-leaning. Dietary preferences are mainly unrestricted (82%), with smaller proportions following specific diets such as flexitarian (7%) and vegetarian (5%). Only 2% identify as vegans, which is closely aligned with the overall UK population (YouGov, 2024). Moreover, the experimental groups are balanced on observable variables; see Appendix Table A1 for balance tables and summary statistics.

[9]For details see: https://www.bi.team/bi-ventures/predictiv/

**Table 1: Sample socio-demographic characteristic**

| | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| Female | .52 | .5 | 0 | 1 |
| Age | 40.42 | 14.18 | 18 | 88 |
| Income | 42273.14 | 27864.33 | 2500 | 100000 |
| Bachelor's degree or higher | .32 | .47 | 0 | 1 |
| ***Location*** | | | | |
| Rural | .16 | .37 | 0 | 1 |
| Suburban | .46 | .5 | 0 | 1 |
| Urban | .37 | .48 | 0 | 1 |
| ***Political Views*** | | | | |
| Left-leaning | .31 | .46 | 0 | 1 |
| Neither left nor right | .46 | .5 | 0 | 1 |
| Right-leaning | .23 | .42 | 0 | 1 |
| ***Diet*** | | | | |
| None in particular | .82 | .38 | 0 | 1 |
| Flexitarian | .07 | .25 | 0 | 1 |
| Pescatarian | .02 | .15 | 0 | 1 |
| Vegetarian | .04 | .21 | 0 | 1 |
| Vegan | .02 | .14 | 0 | 1 |
| Other | .02 | .15 | 0 | 1 |

*Note:* $N = 3,052$.

## 2.7 Estimation

The primary specification used to test our main hypotheses is as follows:

$$Y_{it} = \alpha + \beta_1 \text{Labelling}_i + \beta_2 \text{Repositioning}_i + X_i + e_i \tag{1}$$

where $Y_i$ represents the primary outcomes of interest: $\text{GHG}_i$, $\text{High}_i$, and $\text{Meat}_i$ at time $t$. Outcomes are assessed at three time points: $t = 15s$ (very fast choices), $t = 30s$ (fast choices), and $t = 90s$ (slow choices). $\text{Labelling}_i$ and $\text{Repositioning}_i$ are treatment indicators equal to one if individual $i$ was randomly assigned to the carbon-labelling intervention or menu-repositioning intervention, respectively. $X_i$ is a vector of socio-demographic variables for individual $i$, including age, gender, income, education, device used, and time taken to complete the survey. The latter variable attempts to control for a participant's overall ability and speed in completing survey-based questionnaires, which may be correlated with their ability to navigate the food-delivery app.

We focus our analysis on the following pre-registered outcomes for each individual $i$: (1) GHG emission intensity associated with an individual's food basket ($\text{GHG}_i$), estimated with Ordinary Least Squares (OLS); (2) high carbon footprint meal choices, defined as a binary variable that equals 1 if the selected main meal has a high carbon impact score (D or E) and 0 otherwise (A, B, or C) ($\text{High}_i$), with estimation via a Linear Probability Model (LPM); and (3) meat meal choice, a binary variable equal to 1 if the main meal contains meat and 0 otherwise (vegan, vegetarian, or fish-based) ($\text{Meat}_i$), also analysed with LPM.

Heteroscedasticity-robust (Eicker-Huber-White) standard errors are applied.

The exploratory heterogeneity analysis was conducted following Equation 2:

$$\begin{aligned} Y_i = \alpha + \beta_1 \text{Labelling}_i + \beta_2 \text{Repositioning}_i + \gamma_1 \text{INT1}_i + \delta_1 (\text{INT1}_i \times \text{Labelling}_i) \\ + \delta_2 (\text{INT1}_i \times \text{Repositioning}_i) + \gamma X_i + e_i \end{aligned} \tag{2}$$

where $\text{INT1}_i$ refers to the interaction variable of interest, which enters both as a main effect and is interacted with the treatment indicators ($\text{Labelling}_i$ and $\text{Repositioning}_i$). For ease of interpretation, we plot the predicted differences between the treatment and control groups for each level of the interaction variable, rather than the interaction terms themselves. The full regression outputs, including the interaction terms, are available in the Appendix.

# 3 Results

We begin by presenting an overview of the descriptive statistics and a graphical analysis of consumption choices over time, categorized as 15-second (very fast), 30-second (fast), and 90-second (slow) decisions. We then examine how the interventions (menu-item repositioning and labels) influence participants' consumption choices using OLS and LPM. Following this, we conduct a heterogeneity analysis to determine whether the main results vary across different population segments.

## 3.1 Descriptive statistics

We start by summarizing some key features of the choice task and the choice environment to provide a good understanding of participants' decision-making context. Most participants completed the task at home (82%) using a mobile device (83%). The average first choice was made within 20 seconds (median=17s), and participants made an average of 2.75 subsequent choice revisions. Final revisions were made, on average, at the 53-second mark. Previous studies indicate that hunger can significantly influence decision-making (e.g., Lohmann et al., 2024). In this experiment, the average hunger level of 50 on a 0–100 scale suggests that participants were moderately hungry, potentially impacting their choices. A large portion (46%) found it very easy to choose their preferred option, while only 4% struggled to make a choice, which suggests that the decision environment and the options presented were generally clear and matched expectations of a food-delivery platform.

Table 2: **Food-choice task summary statistics**

| | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| Survey taken at home | .82 | .39 | 0 | 1 |
| Survey taken during work | .22 | .42 | 0 | 1 |
| Mobile | .83 | .38 | 0 | 1 |
| Hungry | 50.47 | 28.04 | 0 | 100 |
| Number of revisions | 2.75 | 3.72 | 0 | 94 |
| Time of first choice (seconds) | 20.29 | 12.81 | 2 | 90 |
| Time of last choice (seconds) | 52.99 | 24.35 | 4 | 90 |
| ***Difficulty finding pref. choice*** | | | | |
| Not at all easy | .04 | .2 | 0 | 1 |
| A little easy | .2 | .4 | 0 | 1 |
| Somewhat easy | .3 | .46 | 0 | 1 |
| Very easy | .46 | .5 | 0 | 1 |

*Note:* $N = 3,052$.

### 3.2 Graphical and regression analysis

Our primary outcome variables are the carbon footprint of the meal order (GHG intensity), whether the meal has a high carbon impact (rated D or E) and if a meat-based main meal was selected. Before proceeding with the regression analysis, we first provide some graphical evidence. Figure 3 depicts the three outcomes in the control and intervention groups separately during the 90-second decision window. The orange bars indicate the distribution of first choices.

All three main outcomes are clearly lowest in the Repositioning group, with a significant difference evident in the first 15 seconds, and they then gradually converge to similar levels as the other interventions after half a minute or more. In fact, repositioning led to significantly lower GHG emissions intensity (4 kg $CO_2$e / kg vs. 6–8 kg $CO_2$e / kg), reduced high-impact choices (around 10% vs. 25–30%), and there were fewer meat meal selections (around 20% vs. 75%) compared to both control and labelling conditions. Furthermore, order effects are most pronounced through quick and intuitive decision-making (first 15 seconds). At the 30-second mark, where approximately 80% of all choices had been made, the differences begin to diminish. By the 90-second endpoint, all three conditions largely converge.[10]

The labelling intervention, interestingly, shows minimal differences in relation to the control group throughout the entire decision window, indicating that carbon footprint labels are, on average, not effective at influencing meal choices compared to structural interventions like menu-item repositioning, nor do they become effective with additional decision time.

[10]Summary statistics for each outcome at the three assessed time points are presented in Appendix Table A2 and illustrated in Appendix Figure A1.

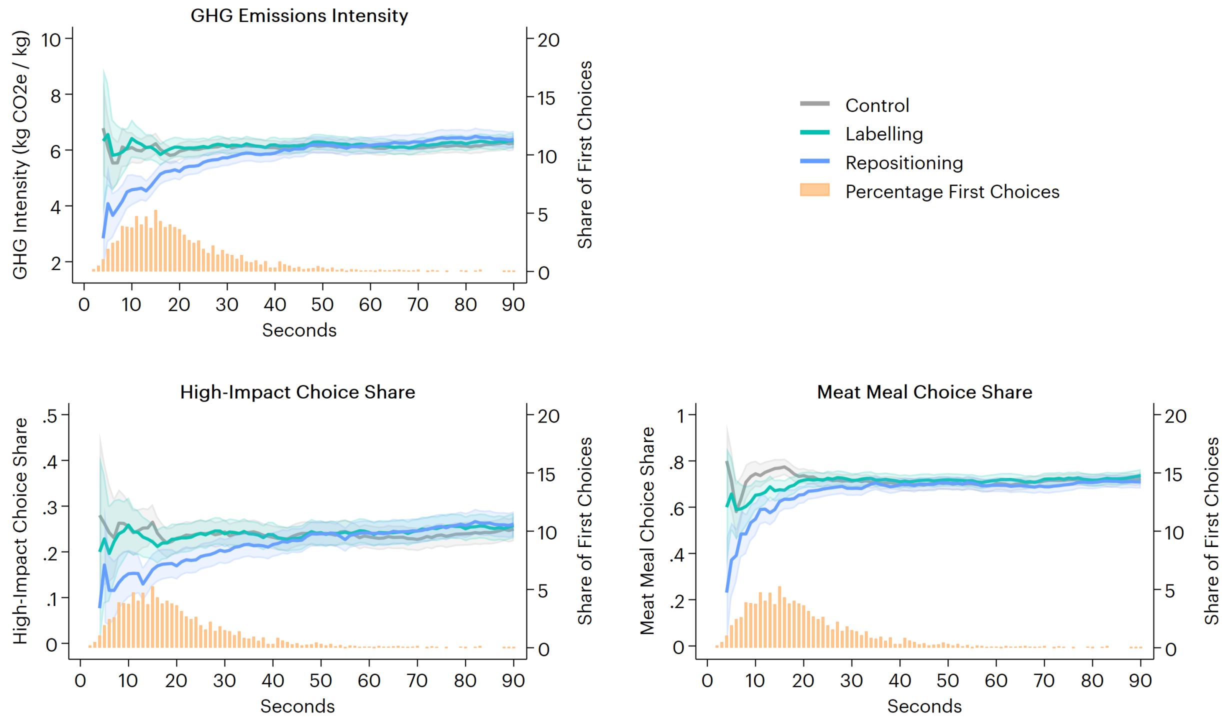


**Figure 3:** Primary outcomes over the entire decision-making window (90 seconds). Note: The orange bars indicate the percentage of first choices. GHG Emissions intensity is measured in kg $CO_2e$ / kg of meal. High-impact and meat meal choice shares range from 0 to 1.

Table 3 reports the estimates of regressing the three main outcome variables on the treatment indicators. We run the regression for the main outcomes at three points: the 15-second, the 30-second and the 90-second marks. Consistent with the graphical evidence, we observe significant treatment effects for the repositioning intervention at the 15- and 30-second intervals, but these effects are not significant at the 90-second mark. More specifically, for very fast choices (15 sec), repositioning reduces GHG emissions intensity by 1.294 kg $CO_2e$ / kg ($p<0.01$), decreases high-impact meal selection by 10.4 percentage points ($p<0.01$) and lowers meat main dish selection by 14.4 percentage points ($p<0.01$). For fast choices (30 seconds), the repositioning effects weaken but remain significant for GHG intensity and high-impact meal selection, while the effect on meat main choices becomes insignificant. For slow choices (90 seconds), all interventions show no statistically significant effects across any outcomes, as indicated by the smaller coefficients and larger standard errors. Note that the sample size increases across time windows (from 1,297 to 2,527 to 3,017 observations), as more participants completed their choices as time progressed.[11] Appendix Table A3 reports estimates for all 'first choices' regardless of their timing (see the orange bars in Figure 3 for their distribution). We find that these estimates are comparable to those of 'very fast' choices.

The regression results also confirm the graphical evidence that carbon labelling has little impact on consumer choices across all time windows and outcome variables. However, there is one statistically

[11]A small number of participants (n=35) emptied their baskets by 90 seconds, after having made an initial choice.

significant effect showing a 9.3 percentage point reduction in meat main selection during very fast choices (15 seconds, $p<0.01$). Yet this effect completely disappears in fast (30 seconds) and slow (90 seconds) decision-making windows. This could be explained by the fact that nearly all red-labelled dishes on the menu were meat options, with only a few exceptions among fish dishes (see Figure A3). The red labels could have acted as a visual warning, quickly steering individuals away from these higher-impact choices without deeper consideration—a response supported by previous evidence on nutritional labelling (Scarborough et al., 2015).

**Table 3: Main Results**

| | Very Fast Choices (15 sec) | | | Fast Choices (30 sec) | | | Slow Choices (90 sec) | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | GHG Intensity | High-impact Main | Meat Main | GHG Intensity | High-impact Main | Meat Main | GHG Intensity | High-impact Main | Meat Main |
| Menu Repositioning | -1.294*** | -0.104*** | -0.144*** | -0.431** | -0.043** | -0.026 | 0.162 | 0.013 | -0.011 |
| | (0.279) | (0.028) | (0.031) | (0.210) | (0.020) | (0.022) | (0.207) | (0.019) | (0.020) |
| Carbon Labelling | -0.238 | -0.044 | -0.093*** | -0.039 | -0.005 | 0.008 | 0.092 | 0.008 | 0.017 |
| | (0.296) | (0.029) | (0.030) | (0.213) | (0.021) | (0.022) | (0.199) | (0.019) | (0.020) |
| Observations | 1297 | 1297 | 1297 | 2527 | 2527 | 2527 | 3017 | 3017 | 3017 |

*Note:* Standard errors in parentheses. Estimates of equation (1). LPM used for binary outcomes.
* p < 0.1, ** p < 0.05, *** p < 0.01.

### 3.3 Heterogeneity analysis

Next, we examine whether the treatment effects differ for several subpopulations. We focus on GHG emissions intensity of the chosen meal and explore heterogeneous treatment effects across key socio-demographic characteristics, including gender, income, education and concern about climate change. Figure 4 presents the subgroup-specific treatment effects estimated following equation (2), representing the treatment effects for each subgroup relative to the equivalent group in the control condition. Full regression outputs including interaction terms are presented in Appendix Table A4. Focusing first on menu repositioning, we notice a gender gap in very fast and fast decisions. The repositioning intervention appears slightly more effective for females than males in the 15-second window, but this relationship is reversed at 30 seconds. It becomes clear that participants with lower socio-economic status, based on income and education, are not necessarily more susceptible to nudges, a potential concern voiced in the literature (e.g., Ghesla et al., 2020). While all subgroups respond similarly under very fast decision-making (15 seconds), individuals with higher education and climate concern continue to make lower-carbon choices at 30 seconds, whereas those with lower education and concern have already revised their selections toward higher-carbon options.

Similarly, we find that the labelling intervention appears to be more effective for participants with a degree, above-median income and greater concern about climate change. This suggests that while labelling has limited impact overall, it may resonate more quickly with these subpopulations, likely due to greater environmental awareness or familiarity with carbon footprint information among better educated groups. The results for these subgroups suggest that labelling also engages System 1 processes, potentially serving as a salient decision prompt under time pressure, as its effects diminish and lose statistical significance by 90 seconds.

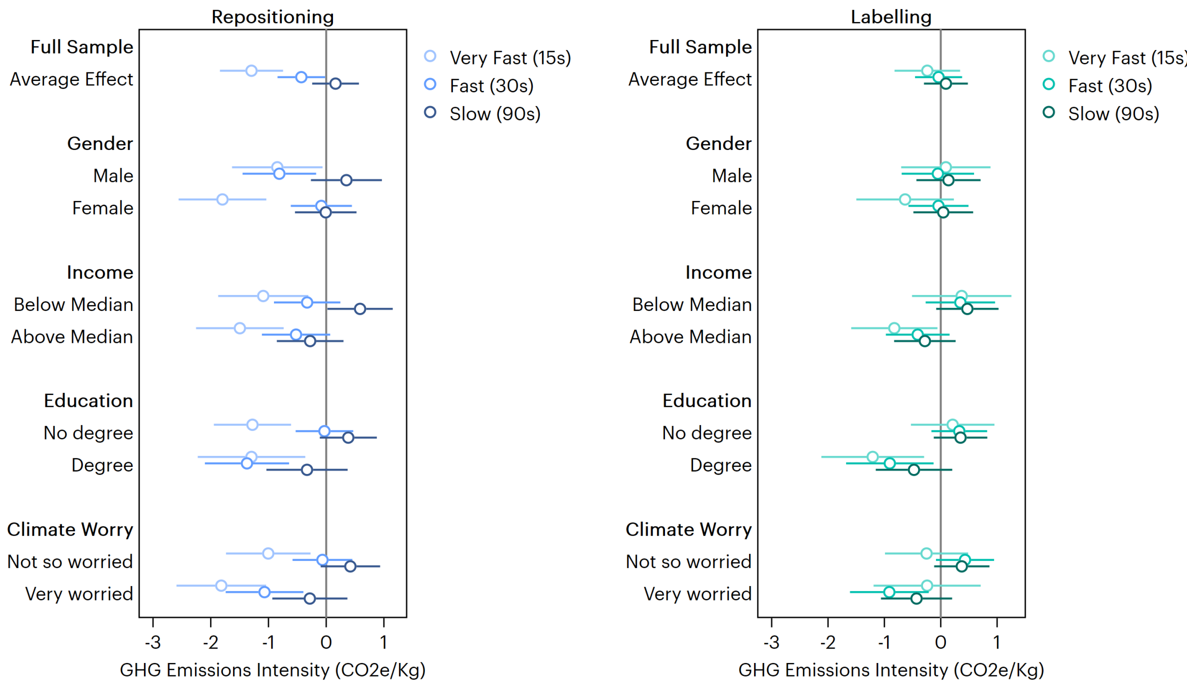


**Figure 4:** Subgroup-specific treatment effects based on equation (2). Error bars represent 95% confidence intervals. Full regression output presented in Appendix Table A4 Average effect of the full sample corresponds to estimates presented in Table 3.

## 4 Discussion and conclusion

Our findings can be summarized into three main insights. First, we find that repositioning affects choices when individuals are making fast, System 1 decisions. We find no heterogenous effects, suggesting that, on average, all participants are affected by repositioning. Second, we find that carbon labels don't affect choices directly, except for individuals who care strongly about the climate and are highly educated. Third, we show that in all three groups, choices converge to high carbon meals when participants are given more time to decide. We will now discuss how these findings relate to the existing literature and what they mean for the implementation of behavioural interventions in practice.

Confirming earlier evidence, our study shows that menu repositioning can be an effective System 1 nudge to promote climate-friendly choices, particularly when decisions for meals are made quickly (Gravert & Kurz, 2021; Kurz, 2018; Lohmann, Gsottbauer, et al., 2024). The nudge achieves an economically and environmentally meaningful reduction in GHG emissions for fast choices, with decreases of 21% at 15 seconds and 7% at 30 seconds into the food choice task. We don't find any significant heterogenous effects for this intervention, showing that the nudge seems to work similarly for everyone when making decisions under time pressure. There are multiple explanations for why repositioning affects choices. The most straight-forward explanation is that repositioning makes it easier to find and choose low-carbon choices. With 83% of participants using their smartphone in our experiment, choosing the restaurant and dishes at the top of the list is faster and easier than scrolling further down the menu. As long as the meals encountered first were regarded as better than no meal, it was in the individuals' best interest to make a first rapid choice and then revise their choice once they find something they like more than their first choice. Choice revisions can subsequently be influenced by for example the endowment effect, where later options are subsequently compared to the first choice (Johnson et al., 2007; Tversky & Kahneman, 2000).

Carbon labels, in contrast, showed minimal impact on carbon intensity of meal choices, on average. This finding is also in line with previous literature (Lohmann, Gsottbauer, et al., 2024; Maier & Fesenfeld, 2024; Muller et al., 2019). We propose two main explanations for the lack of effect in our setting: Either, participants did not notice the labels, or, they noticed them, but decided not to use the information.[12] From our post-experimental survey, we learn that only 30% of participants in the labelling condition reported noticing the carbon footprint labels, supporting the first explanation. This lack of perception is surprising, as we pretested the employed carbon label intensively. The label was designed according to the most recent insights on effective label design (Thøgersen et al., 2024) and pretesting found that it is well-suited to convey the information intended. We can therefore largely rule out that participants did not understand the labels. The difference in label effectiveness in the pre-test and the experiment is not atypical for laboratory experiments, where the focus is solely on the label. In a real-life context such as in a food delivery platform, carbon labels compete for attention with other relevant information such as prices, meal descriptions, photos, ads, and so on. Even well-designed labels may fail to be salient enough to cut through the information noise and capture consumers' attention.

However, we also find evidence that is in line with the second explanation of choosing not to use the information. The average participant in our study appears to have limited environmental preferences for climate-friendly food choices: Only 15% indicated in the pre-intervention survey that it was "very important" for their food consumption to be climate-friendly, and only 5% stated "climate" as a factor influencing their decision after completing the task. If environmental factors are not a priority for consumers, then information on climate impact may lack relevance, which could explain why labelling did not significantly affect choices. This phenomenon of ignoring information not perceived as relevant to one's own decision utility is known in economics as "rational inattention" (Maćkowiak et al., 2023; Sims, 2003). This concept is, however, anything but new: Daniel Kahneman discussed the observation that attention is effortful and that therefore individuals select what things to pay attention to, more than fifty years ago in "Attention and Effort" (Kahneman, 1973).

In our experiment, individuals could choose to ignore the labels and focus on either meal descriptions or prices. However, rational inattention theory also explains why certain groups did respond to the climate

[12] One could also imagine that some individuals may interpret labels as attempt to manipulate their choices by inducing guilt, prompting reactance behaviour (e.g. intentionally choosing a red-labelled meal). However, we find no evidence of this, as the proportion of high carbon choices is similar to that of the control condition.

labels when making fast choice - namely, those with higher income, higher education, or strong climate consciousness, factors which are likely to be correlated. In other words, when people care about making climate-conscious decisions (or have the means and education to do so), they seem to use the labels as a decision heuristic, especially when decision time is limited. By "fast"-checking the labels, they can avoid making 'red' choices that warn them of high climate impact meals, or they can focus on 'green' choices that could even have a rewarding effect: choosing green might make them feel good about doing the right thing (Lohmann et al., 2022; Schwartz et al., 2020). Future research could investigate the exact mechanism using, e.g., eye tracking methods. Yet, whether choices are fast or slow, expectations of the direct effects of carbon labels on consumer choice should be modest. As food policy scholars have argued, the real potential of labels might lie in their indirect effects on the supply side, with industry, retail, and online platforms adapting processes, reformulating menus or recipes with the aim of avoiding unattractive 'red' labels (Robertson et al., 2023).

For both interventions, we find that the choices converge toward high-emission meals over time and become indistinguishable from those in the baseline group without any intervention. This reversion raises the question of whether the repositioning nudge works as originally intended as a tool to "help people make better choices as judged by themselves" (Thaler & Sunstein, 2008). The original premise of nudging, as introduced by Thaler & Sunstein (Thaler & Sunstein, 2008), also known as asymmetric paternalism (Camerer et al., 2003), was that it "creates large benefits for those who make errors, while imposing little or no harm on those who are fully rational." In our setting this would imply that individuals make mistakes when they choose quickly (System 1) but would not be making these mistakes when choosing slowly (System 2). The nudge should help them make the "right" choice, that is, the choice aligned with the decision makers' preferences, also under time pressure. This seems not to be the case in our study.

Consider the following thought experiment: The same intervention, repositioning menu items, could be used for three purposes: (1) to increase the utility of the choice architect (business as choice architect), by, for example, placing more expensive items at the top of the list to maximise profits; (2) to increase the utility of the individual consumer by overcoming an internality (regulator as choice architect) by placing healthier food options at the top; or (3) to increase the utility of society by reducing externalities from choices by placing lower carbon items at the top. Options 2 and 3 are both in line with the definition of nudging as 'welfare enhancing intervention'. While it is plausible that in all three cases the incentives of the choice architect and the decision maker are aligned, it seems more likely that, after deliberation, the decision maker realizes that in case (1) and (3), they would prefer a different meal than the one nudged toward, prompting a change in choice. Given that we observe a convergence toward higher-carbon choices in both treatment groups and control eventually, it seems that the choice architects' and the decision makers' preferences were not aligned. If they were aligned and participants were 'making mistakes', we should have seen low carbon choices for the fast choices and fewer choice revisions for the repositioning group. The control and labelling group should have converged to the same lower emissions average over time. However, we find that all three groups revise their choices equally often (Control: 2.96, Repositioning: 2.64, Labelling: 2.62) and ultimately select higher-emission meal. Instead of "correcting a mistake", the repositioning intervention appears to nudge choices temporarily toward lower-carbon options.

Whether this is good or bad depends on the point of view of the regulator. If we are aiming to maximize individual welfare, then the repositioning nudge was 'bad' and the carbon labels which only influenced the choices of those who care about the climate are 'good'. If, however, the aim of the nudge is to reduce externalities on society, as is the case of 'green nudges' (Carlsson et al., 2021), then the repositioning nudge was a success, and the carbon labels were ineffective, on average.

In a nutshell, our results imply that choice architects should be aware that encouraging climate-friendly food choices through repositioning or labelling (i.e., green nudges or prosocial nudges) might stand in contrast to what individuals would prefer to consume if they had time to deliberate. While repositioning is more effective and seems to be widely accepted (Sunstein & Reisch, 2019), it is less visible and transparent than climate labels and hence calls for a particularly responsible approach by regulators and platforms alike, such as, informing customers about the intention to guide their choices towards less climate-intensive options (Bruns et al., 2018; Michaelsen, 2023).

If the goal is to decrease environmental or climate externalities through the choice architecture, both interventions will work best in context where consumers make rapid decisions. In most cases, it will not be feasible or ethical to deliberately impose time pressure. Nevertheless, there are many plausible endogenous and exogenous factors that can naturally lead individuals to make decisions more quickly or slowly. For instance, the hectic environment of a coffee shop during Monday morning rush hour will encourage faster decisions than the same coffee shop on a quiet Sunday evening. Similarly, a person running late for work will make faster decisions than a tourist taking shelter from the rain.

Therefore, choice architects should interpret our results both as an explanation for the size of repositioning effects and as guidance on the types of settings where implementing these nudges would be most appropriate. The more fast choices they expect to naturally occur, the larger the effects they should expect. This perspective could explain the relatively large effects of menu repositioning observed in a lunch restaurant (Gravert & Kurz, 2021), a university canteen (Kurz, 2018) or a food delivery app (Lohmann, Gsottbauer, et al., 2024). More broadly, our findings suggest that decision-making speed may be an overlooked factor contributing to the substantial unobserved heterogeneity observed in the literature (Lohmann, Pizzo, et al., 2024; Szaszi et al., 2018, 2022). Research on behavioural interventions should thus place a stronger focus on decision-making speed when evaluating their effectiveness. Nudging fast, or slow, may be one important piece of the puzzle in fully understanding how to design interventions that are both effective and consistent across contexts (Szaszi et al., 2022).

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# A1 Additional Tables

**Table A1: Balance Checks**

| | Control n=1,070 (35.1%) | Carbon Labelling n=995 (32.6%) | p-value | Menu Repositioning n=987 (32.3%) | p-value |
|---|---|---|---|---|---|
| Mobile | 0.83 (0.38) | 0.84 (0.37) | 0.500 | 0.83 (0.38) | 0.983 |
| Survey Duration | 755.11 (1740.55) | 657.07 (716.19) | 0.099 | 680.11 (961.90) | 0.232 |
| Female | 0.51 (0.50) | 0.51 (0.50) | 0.979 | 0.53 (0.50) | 0.535 |
| Age | 41.17 (14.51) | 39.91 (13.89) | 0.043 | 40.13 (14.09) | 0.099 |
| Income (mid) | 41802.10 (27276.82) | 43615.95 (28176.29) | 0.137 | 41430.09 (28155.32) | 0.761 |
| Degree | 0.30 (0.46) | 0.34 (0.48) | 0.047 | 0.32 (0.47) | 0.319 |
| ***Political Views*** | | | | | |
| Left leaning | 325 (30.4%) | 302 (30.4%) | 0.999 | 323 (32.7%) | 0.461 |
| Neither left nor right | 497 (46.4%) | 463 (46.5%) | | 451 (45.7%) | |
| Right leaning | 248 (23.2%) | 230 (23.1%) | | 213 (21.6%) | |
| ***Diet*** | | | | | |
| None in particular | 883 (82.5%) | 823 (82.7%) | 0.299 | 801 (81.2%) | 0.584 |
| Flexitarian | 67 (6.3%) | 72 (7.2%) | | 74 (7.5%) | |
| Pescatarian | 27 (2.5%) | 15 (1.5%) | | 24 (2.4%) | |
| Vegetarian | 40 (3.7%) | 47 (4.7%) | | 48 (4.9%) | |
| Vegan | 24 (2.2%) | 18 (1.8%) | | 19 (1.9%) | |
| Other | 29 (2.7%) | 20 (2.0%) | | 21 (2.1%) | |

*Note:* Table displays summary statistics and balance checks for key socio-demographic variables. P-value column displays the p-value from balance tests between the control group and the respective treatment group. Means and standard deviations (in parentheses) and p-value from linear regression displayed for continuous variables. Frequency and percent (in parentheses) and p-values from Pearson Chi-squared test displayed for categorical variables.

**Table A2: Summary Statistics of primary outcomes for 'very fast', 'fast' and 'slow' decision-making**

| | Control | | | Carbon Labelling | | | Menu Repositioning | | |
|---|---|---|---|---|---|---|---|---|---|
| | Mean | SD | N | Mean | SD | N | Mean | SD | N |
| **GHG Emissions Intensity** | | | | | | | | | |
| 15 Seconds | 6.23 | (4.33) | 468 | 5.99 | (4.52) | 419 | 4.93 | (3.87) | 410 |
| 30 Seconds | 6.17 | (4.40) | 911 | 6.12 | (4.40) | 810 | 5.72 | (4.29) | 806 |
| 90 Seconds | 6.25 | (4.47) | 1057 | 6.32 | (4.46) | 983 | 6.39 | (4.82) | 977 |
| **High-Impact Meals** | | | | | | | | | |
| 15 Seconds | 0.26 | (0.44) | 468 | 0.22 | (0.42) | 419 | 0.16 | (0.37) | 410 |
| 30 Seconds | 0.24 | (0.43) | 911 | 0.24 | (0.43) | 810 | 0.20 | (0.40) | 806 |
| 90 Seconds | 0.25 | (0.43) | 1057 | 0.26 | (0.44) | 983 | 0.26 | (0.44) | 977 |
| **Meat Meals** | | | | | | | | | |
| 15 Seconds | 0.77 | (0.42) | 468 | 0.68 | (0.47) | 419 | 0.62 | (0.48) | 410 |
| 30 Seconds | 0.71 | (0.45) | 911 | 0.72 | (0.45) | 810 | 0.68 | (0.47) | 806 |
| 90 Seconds | 0.72 | (0.45) | 1057 | 0.73 | (0.44) | 983 | 0.71 | (0.45) | 977 |

*Note:* Table displays summary statistics for primary outcomes by treatment condition for each decision-making speed: very fast (15 seconds), fast (30 seconds), slow (90 seconds).

**Table A3: Main analysis for first choices**

| | First Choices | | |
|---|---|---|---|
| | (1) GHG Intensity | (2) High-impact Main | (3) Meat Main |
| Menu Repositioning | -1.039*** | -0.068*** | -0.100*** |
| | (0.183) | (0.018) | (0.021) |
| Carbon Labelling | 0.102 | -0.002 | -0.006 |
| | (0.193) | (0.019) | (0.020) |
| Observations | 3052 | 3052 | 3052 |

*Note:* Table displays estimates of equation (1). Standard errors in parentheses. LPM used for binary outcomes (columns 2 and 3).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

**Table A4: Heterogeneity Analysis**

| | Full Sample | | | Female | | | Income | | | Education | | | Climate Worry | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
| | Very Fast | Fast | Slow | Very Fast | Fast | Slow | Very Fast | Fast | Slow | Very Fast | Fast | Slow | Very Fast | Fast | Slow |
| Labelling | -0.238 | -0.039 | 0.092 | 0.090 | -0.051 | 0.137 | 0.372 | 0.348 | 0.472* | 0.212 | 0.329 | 0.351 | -0.252 | 0.431 | 0.374 |
| | (0.296) | (0.213) | (0.199) | (0.404) | (0.328) | (0.291) | (0.450) | (0.314) | (0.282) | (0.378) | (0.252) | (0.242) | (0.376) | (0.263) | (0.250) |
| Repositioning | -1.294*** | -0.431** | 0.162 | -0.847** | -0.811** | 0.351 | -1.090*** | -0.330 | 0.587** | -1.277*** | -0.030 | 0.383 | -1.004*** | -0.065 | 0.420 |
| | (0.279) | (0.210) | (0.207) | (0.400) | (0.325) | (0.314) | (0.398) | (0.293) | (0.289) | (0.341) | (0.255) | (0.252) | (0.373) | (0.264) | (0.263) |
| INT | | | | 0.076 | -0.867*** | -0.510* | 0.557 | 0.280 | 0.809*** | -0.293 | 0.374 | 0.039 | -0.310 | 0.504 | 0.021 |
| | | | | (0.409) | (0.292) | (0.278) | (0.407) | (0.291) | (0.276) | (0.427) | (0.338) | (0.305) | (0.411) | (0.311) | (0.288) |
| INT × Labelling | | | | -0.723 | 0.011 | -0.093 | -1.195** | -0.756* | -0.754* | -1.419** | -1.232*** | -0.826* | 0.010 | -1.342*** | -0.803** |
| | | | | (0.601) | (0.425) | (0.396) | (0.596) | (0.425) | (0.395) | (0.601) | (0.469) | (0.421) | (0.612) | (0.442) | (0.406) |
| INT × Repositioning | | | | -0.950* | 0.727* | -0.358 | -0.405 | -0.192 | -0.865** | -0.017 | -1.342*** | -0.715 | -0.813 | -1.003** | -0.702* |
| | | | | (0.557) | (0.422) | (0.415) | (0.553) | (0.420) | (0.412) | (0.583) | (0.451) | (0.438) | (0.544) | (0.432) | (0.422) |
| Female | -0.456* | -0.656*** | -0.646*** | 0.000 | 0.000 | 0.000 | -0.475** | -0.635*** | -0.661*** | -0.435* | -0.621*** | -0.651*** | -0.407* | -0.619*** | -0.637*** |
| | (0.240) | (0.175) | (0.170) | | | | (0.240) | (0.174) | (0.170) | (0.241) | (0.175) | (0.170) | (0.239) | (0.173) | (0.170) |
| Age | -0.007 | 0.003 | 0.005 | -0.006 | 0.002 | 0.005 | -0.007 | 0.003 | 0.005 | -0.007 | 0.002 | 0.005 | -0.005 | 0.003 | 0.006 |
| | (0.008) | (0.006) | (0.006) | (0.008) | (0.006) | (0.006) | (0.008) | (0.006) | (0.006) | (0.008) | (0.006) | (0.006) | (0.008) | (0.006) | (0.006) |
| High Edu (Degree) | -0.779*** | -0.411** | -0.500*** | -0.774*** | -0.460** | -0.472*** | -0.788*** | -0.472** | -0.467*** | 0.000 | 0.000 | 0.000 | -0.720*** | -0.432** | -0.427** |
| | (0.252) | (0.191) | (0.181) | (0.250) | (0.188) | (0.178) | (0.248) | (0.189) | (0.178) | | | | (0.249) | (0.189) | (0.178) |
| Mobile | 0.032 | 0.109 | 0.513** | 0.039 | 0.116 | 0.504** | 0.058 | 0.127 | 0.497** | 0.067 | 0.115 | 0.503** | -0.021 | 0.098 | 0.474** |
| | (0.306) | (0.236) | (0.220) | (0.306) | (0.235) | (0.219) | (0.306) | (0.236) | (0.219) | (0.305) | (0.236) | (0.218) | (0.309) | (0.236) | (0.220) |
| Survey Duration | 0.000 | -0.000** | -0.000 | 0.000 | -0.000** | -0.000 | 0.000 | -0.000*** | -0.000 | 0.000 | -0.000*** | -0.000 | 0.000 | -0.000** | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| High Income | | | | 0.029 | -0.021 | 0.285* | 0.000 | 0.000 | 0.000 | 0.025 | -0.018 | 0.289* | 0.068 | -0.025 | 0.287* |
| | | | | (0.243) | (0.175) | (0.170) | | | | (0.243) | (0.176) | (0.171) | (0.242) | (0.175) | (0.170) |
| Constant | 6.800*** | 6.635*** | 5.876*** | 6.550*** | 6.631*** | 5.917*** | 6.550*** | 6.344*** | 5.737*** | 6.641*** | 6.283*** | 5.852*** | 6.879*** | 6.282*** | 5.938*** |
| | (0.514) | (0.399) | (0.377) | (0.522) | (0.413) | (0.383) | (0.525) | (0.406) | (0.379) | (0.509) | (0.390) | (0.372) | (0.533) | (0.397) | (0.379) |
| $R^2$ | 0.027 | 0.010 | 0.009 | 0.029 | 0.011 | 0.009 | 0.030 | 0.011 | 0.011 | 0.032 | 0.014 | 0.010 | 0.032 | 0.015 | 0.013 |
| Observations | 1,297 | 2,527 | 3,017 | 1,297 | 2,527 | 3,017 | 1,297 | 2,527 | 3,017 | 1,297 | 2,527 | 3,017 | 1,297 | 2,527 | 3,017 |

*Note:* Table displays estimates of equation (2). Standard errors in parentheses. The interaction variable of interest is presented in the column header and estimated for each decision-making speed: very fast (15 seconds), fast (30 seconds), slow (90 seconds). The outcome variable is the GHG Emissions Intensity (kg $CO_2$e / Kg) of the chosen meal in all columns.

* p < 0.1, ** p < 0.05, *** p < 0.01.

**Table A5: Incentivisation Summary Statistics**

| | |
|---|---|
| Winners contacted | 118 |
| Could not be contacted | 5 |
| No response | 49 |
| Incomplete response | 2 |
| Deliveroo/Restaurant/Item unavailable | 20 |
| Successful deliveries | 34 |
| Failed deliveries | 3 |
| Total Delivery Cost | £593.4 |
| Total Email Payments | £1191.33 |
| Total Charity Donation | £160 |
| Total Incentivisation | 1,944.73 |

## A2 Additional Figures

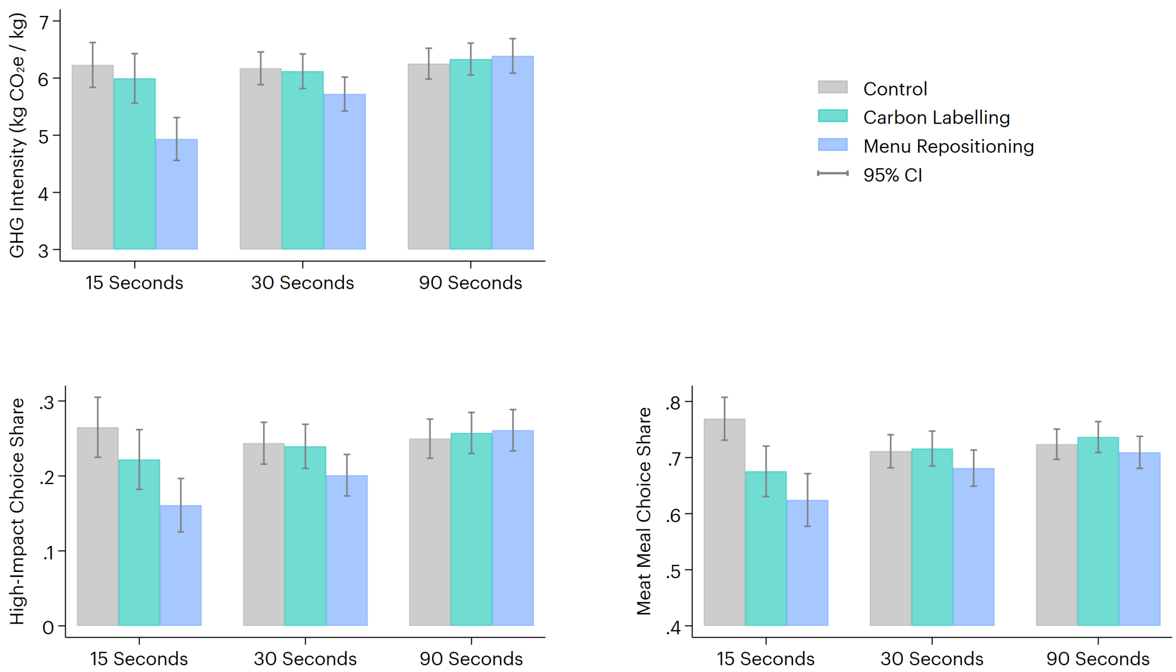


**Figure A1:** Primary outcomes by treatment condition and decision-making speed. Error bars are 95% confidence intervals.

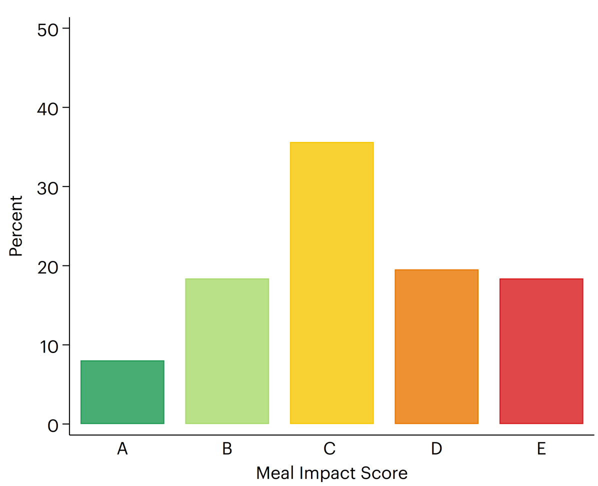


**Figure A2:** Distribution of impact scores (A–E) for all meals available on the platform (n=87).

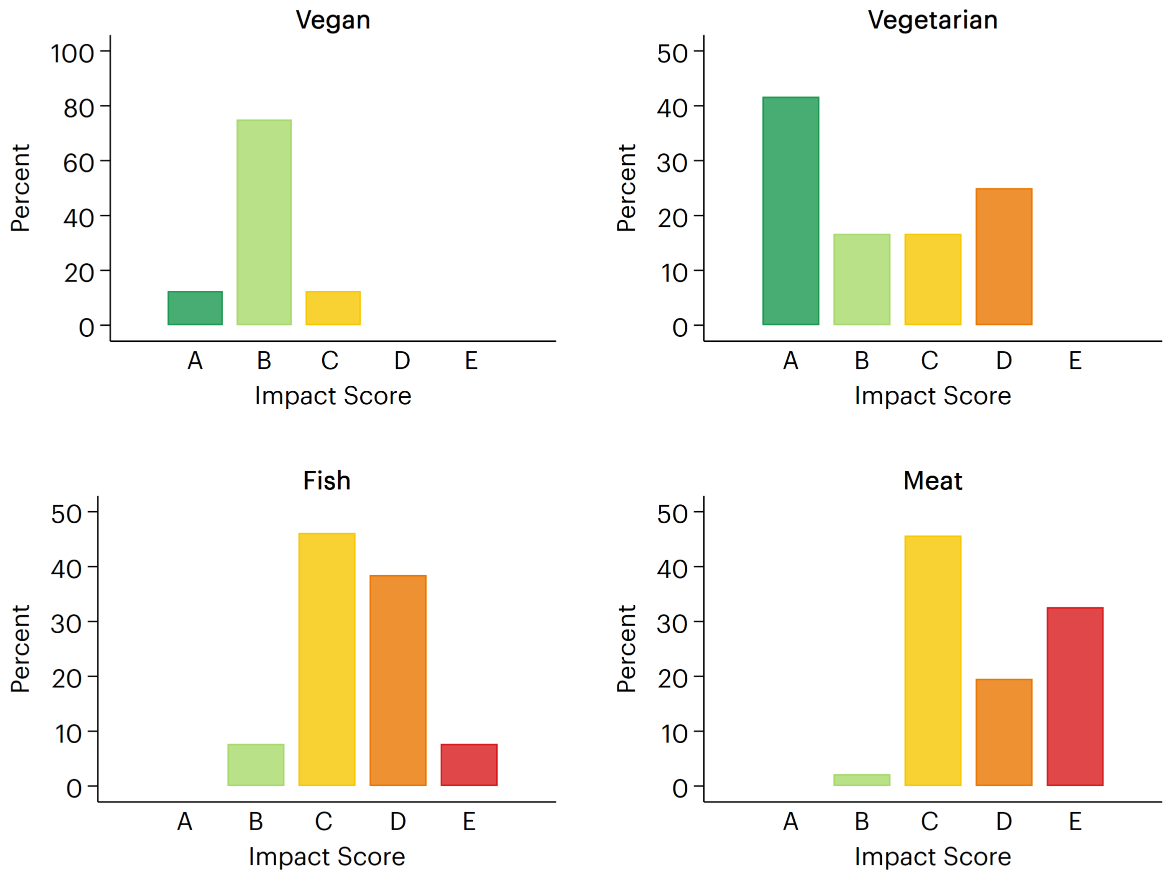


**Figure A3:** Distribution of impact scores (A–E) across each meal type category.

## A3 Experimental Instructions

### General Study Information

The aim of this study is to study food purchasing on online food delivery platforms. You have been invited to take part because you are aged 18 and over and have previously used online delivery platforms.

This study contains a short survey where we will ask you some questions about yourself and your food consumer behaviour and attitudes to purchase food online. You will then be asked to order food for dinner. Note that for some of you this order will have real consequences, as every 30th participant will actually receive the ordered food which will be delivered to their homes. In total, we expect 4000 participants to complete this study.

No background knowledge is required to complete the study. The study will take about 5–10 minutes to complete.

### Task Instructions

**Your task:** In this next section, we want you to imagine you are ordering dinner for yourself on an online delivery platform. You will be given a virtual budget of £20 to spend on our online food delivery platform. It is important that you make a careful choice, as there is a chance you will actually receive the order you place, and if selected as a winner, we will also pay you the remainder of your budget via bank transfer. You can use our food delivery platform just like you would in real life: you can browse through multiple restaurants, view their menus, and add or remove foods from your basket.

**How we record your choices:**

- You will have 90 seconds to add items to your basket.
- If you add a new item, it will replace the current item in your basket.
- You cannot check out before time is up, but all your choices are saved.
- A bar on the top or bottom shows the remaining time.

**After 90 seconds:**

- You will be checked out automatically.
- A random second between 10 and 90 will be chosen.
- The item in your basket at that moment will be the ordered meal.

- If your basket is empty at that second, you won't receive a meal or payout.
- It's in your best interest to make a quick, possibly provisional choice by 10 seconds to avoid getting nothing. You can always change your mind later, as often as you like.

**Meal prize draw:**

- A random draw (1 out of 30) will determine meal winners.
- You will be notified if you are selected at the end of the survey.
- Winners will be contacted by email after the study and can choose a date and time for meal delivery.
- Your remaining budget will be paid out via bank transfer.

### Comprehension Check

Before you place your order on the meal delivery app, please answer the following questions:

1. How many seconds do you have to make meal choices on the app? *Answers: a) 60s, b) 90s, c) 120s*
2. Can you change your mind by removing and re-adding items to the basket? *Answers: a) Yes, as many times as I like; b) Yes, but only twice; c) No*
3. What determines your ordered meal? *Answers: a) The item in your basket at a randomly drawn second between 10 and 90; b) The first item you added; c) The last item you added.*
4. If you made a first choice after 30 seconds and the randomly drawn second is 15, what is your ordered meal? *Answers: a) A random meal; b) your chosen meal; c) No meal*
5. If you made a first choice after 30 seconds and the randomly drawn second is 39, what is your ordered meal? *Answers: a) A random meal; b) your chosen meal; c) no meal*
6. If you changed your meal to a different one after 60 seconds and the randomly drawn second is 46, what is your ordered meal? *Answers: a) your first choice; b) your second choice; c) no meal*
7. If you changed your meal to a different one after 60 seconds and the randomly drawn second is 78, what is your ordered meal? *Answers: a) your first choice; b) your second choice; c) no meal*

## A4 Questionnaire

### Pre-Survey

1. Where are you right now while taking this survey? *[At work; at home (not working); at home (working); traveling (e.g., commuting, on a trip); during leisure time (e.g., at a cafe, park, social event, with family/friends); other (please specify)]*
2. How hungry are you feeling right now? *[0 - "Not at all hungry" to 100 - "Extremely hungry"]*
3. How frequently do you get an online takeaway (i.e., takeaway food order at platforms like Just Eat or Deliveroo)? *[A few times a year; At least once a month; At least 3–4 times a month; Twice a week; More than twice a week]*
4. If you get an online takeaway, you usually have it... *[On my own; With friends; With family; With colleagues (at work); Not sure—it varies]*
5. What diet do you follow, if any? *[None in particular; Vegan; Vegetarian; Flexitarian; Pescatarian; Other (please specify)]*.
6. How often do you eat a sweet dessert with your meals? *[Every day; Between 3–5 times a week; 1–2 times a week; Less than once a week; Never]*
7. How often do you eat meat or fish? (including sausage, salami, steak etc). *[Every day; Between 3–5 times a week; 1–2 times a week; Less than once a week; Never]*
8. How important is it that the food you normally choose is healthy? *[1: Not at all important - 4: very important]*
9. How important is it that the food you normally choose is climate friendly? *[1: Not at all important - 4: very important]*
10. How important is it that the food you normally choose is cheap? *[1: Not at all important - 4: very important]*
11. How important is it that the food you normally choose is tasty? *[1: Not at all important - 4: very important]*
12. Some people in Britain tend to identify more with the political left, while others tend to identify more with the political right. In general, which side do you identify with more? *[Strongly left; Moderately left; Slightly left; Neither the left nor the right; Slightly right; Moderately right; Strongly right]*
13. If you are running a race and you are passing the person in the second place, which place are you in?

14. A bat and a ball cost 22 dollars in total. The bat costs 20 dollars more than the ball. How many dollars does the ball cost?

15. If it takes 7 machines 7 minutes to make 7 widgets, how many minutes would it take 100 machines to make 100 widgets?

### Post-Survey

1. How easy did you find it to find your preferred meal? *[Not at all satisfied; Not very satisfied; Neither unsatisfied nor satisfied; Satisfied; Very satisfied]*

2. Which factors most influenced your food choice? *[Select all that apply] Multiple choice [Taste; craving; quality; price (value for money); climate impact; animal welfare concerns; ethics; other environmental concerns (water pollution, air pollution, land use change, biodiversity loss); portion size; cuisine; nutritional content; health; cultural/religious reasons; none of the above; other (please specify).]*

3. Do you recall seeing any of the following labels on the menu? *[Multiple choice - Calorie labels; organic labels; carbon labels; fair trade labels.]*

4. How worried are you about climate change? *[Not at all worried - Extremely worried]*

5. How worried are you about your health? *[Not at all worried - Extremely worried]*

6. To what extent do you feel a personal responsibility to try to reduce climate change? *[0 - Not at all; 10 = A great deal]*

7. To what extent do you feel a personal responsibility to adopt habits that promote a healthy lifestyle? *[0 - Not at all; 10 = A great deal]*

8. AHS-4 items, 1 (“strongly disagree”) to 7 (“strongly agree”) *[Please indicate your level of agreement with each of the following statements: everything in the universe is somehow related to each other; it is more desirable to take the middle ground than go to extremes; future events are predictable based on present situations; it is more important to pay attention to the whole context rather than the details.]*

9. Love of variety: 5-point Likert scale, ranging from "completely disagree" to "completely agree". Item 7 is reverse-scored. *[When I eat out, I like to try the most unusual items, even if I am not sure I would like them; While preparing foods or snacks, I like to try out new recipes; I think it is fun to try out food items one is not familiar with; I am eager to know what kinds of foods people from other countries eat; I prefer to eat food products I am used to. (reverse-scored)]*

# A5 Label Pre-test Results

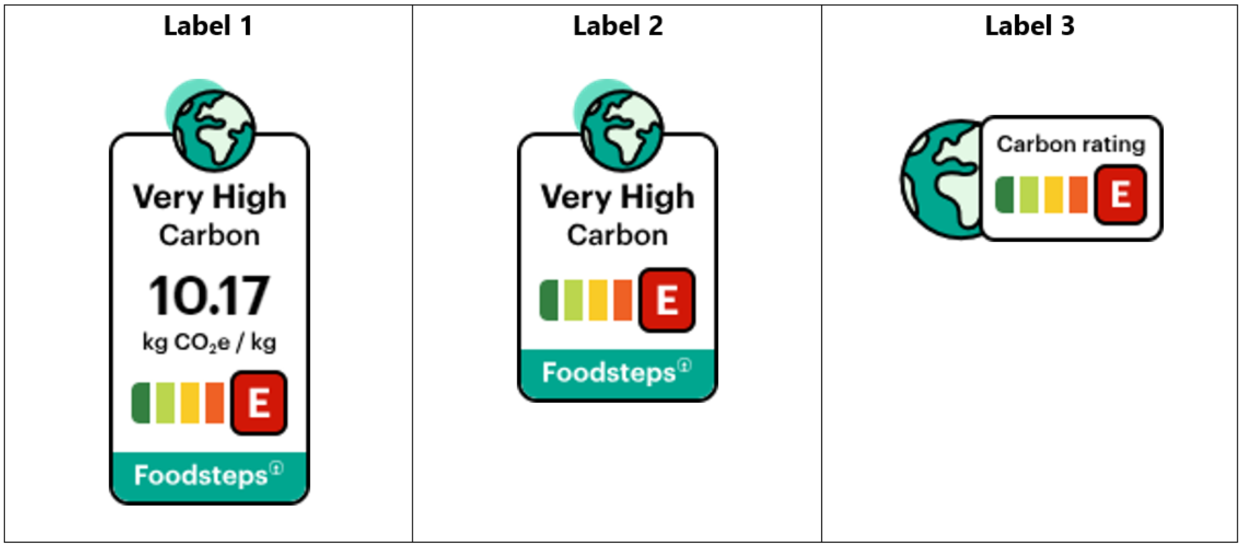


**Figure A4:** Labels tested in the label pre-test survey.

**Table A6: What does the label show?**

| | Label 1 | Label 2 | Label 3 |
|---|---|---|---|
| The climate impact of the meal | 90% | 84.5% | 84% |
| | (45) | (38) | (42) |
| The energy required to prepare the meal | 10% | 13.3% | 14% |
| | (5) | (6) | (7) |
| The healthiness of the meal | | 2.2% | 2% |
| | | (1) | (1) |
| Observations | 50 | 45 | 50 |

*Note:* Percentage responses per category. Number of responses (in parentheses) differ due to enforced time pressure (30 seconds). Initial allocation of participants to each group: Label 1 = 50, Label 2 = 46, Label 3 = 51

**Table A7: Ratings under time pressure**

| | Label 1 | Label 2 | Label 3 |
|---|---|---|---|
| Info provided | 6.35 | 6.72 | 5.72 |
| | (43) | (43) | (46) |
| Clear/Concise | 6.48 | 6.75 | 6.43 |
| | (42) | (40) | (44) |
| Easy to understand | 6.14 | 7.36 | 6.11 |
| | (37) | (36) | (37) |
| Trustworthy | 5.20 | 5.81 | 5.94 |
| | (30) | (32) | (32) |
| Visual appeal | 6.33 | 5.85 | 6.83 |
| | (24) | (26) | (29) |
| Appropriate for apps | 6.00 | 6.15 | 6.39 |
| | (19) | (20) | (23) |
| Average score | 6.20 | 6.58 | 6.05 |
| | (43) | (43) | (48) |

*Note:* Average score per item and overall average score under time pressure (30 seconds). Items were scored on a scale of 0–10. Number of responses (in parentheses) differs due to enforced time pressure (30 seconds). Initial allocation of participants to each group: Label 1 = 50, Label 2 = 46, Label 3 = 51

**Table A8: Ratings without time pressure**

| | Label 1 | Label 2 | Label 3 |
|---|---|---|---|
| Info provided | 7.65 | 5.96 | 5.71 |
| | (2.06) | (2.35) | (2.35) |
| Clear/Concise | 7.15 | 6.36 | 6.32 |
| | (2.14) | (2.51) | (2.61) |
| Easy to understand | 6.76 | 6.23 | 6.11 |
| | (2.48) | (2.69) | (2.66) |
| Trustworthy | 6.42 | 5.67 | 5.25 |
| | (2.48) | (2.74) | (2.55) |
| Visual appeal | 6.60 | 6.66 | 6.28 |
| | (2.56) | (2.45) | (2.40) |
| Appropriate for apps | 5.91 | 5.71 | 5.27 |
| | (2.83) | (2.96) | (3.07) |
| Average score | 6.57 | 6.13 | 5.85 |
| | (2.08) | (2.12) | (2.11) |
| Observations | 97 | 101 | 96 |

*Note:* Average score per item and overall average score, without time pressure. Items were scored on a scale of 0–10. Standard deviation in parentheses.

**Table A9: Ranking**

| | Label 1 | Label 2 | Label 3 |
|---|---|---|---|
| First | 70 | 52 | 25 |
| Second | 32 | 71 | 44 |
| Third | 45 | 24 | 78 |
| Overall Score | 147 | 147 | 147 |
| Observations | 147 | 147 | 147 |

*Note:* Number of times a label was chosen as First, Second or Third, without time pressure. Average Score based on allocating 3 points for First, 2 points for Second and 1 point for Third.