Impact of calorie labelling on online takeaway food choices: an online Menu-Based Choice Experiment in England

Appetite 207 (2025) 107894

Contents lists available at ScienceDirect

Appetite

journal homepage: www.elsevier.com/locate/appet

Impact of calorie labelling on online takeaway food choices: An online Menu-Based Choice Experiment in England

Oana-Adelina Tanasache [a,*], Cherry Law [b], Richard D. Smith [c], Steven Cummins [a], Esther W. de Bekker-Grob [d], Joffre Swait [d,f], Bas Donkers [e], Laura Cornelsen [a]

[a] *Department of Public Health, Environments and Society, London School of Hygiene & Tropical Medicine, 15-17 Tavistock Place, WC1H 9SH, London, UK*
[b] *Department of Agri-Food Economics and Marketing, University of Reading, Whiteknights House, Reading, RG6 6UR, UK*
[c] *Medical School, University of Exeter. B3183, Exeter, EX1 2HZ, UK*
[d] *Erasmus School of Health Policy & Management, Erasmus University Rotterdam, Burgemeester Oudlaan 50, 3062 PA, Rotterdam, Netherlands*
[e] *Erasmus School of Economics, Erasmus University Rotterdam, Burgemeester Oudlaan 50, 3062 PA, Rotterdam, Netherlands*
[f] *Erasmus School of Health Policy & Management, Erasmus Choice Modelling Centre, and Erasmus Centre for Health Economics, Erasmus University Rotterdam, P.O. Box 1738, 3000 DR Rotterdam, The Netherlands*

ARTICLE INFO

Keywords:
Food choice
Online takeaway
Calorie label
Price elasticity

ABSTRACT

Eating out-of-home is linked to higher calorie intake and body weight, risk factors for obesity, diabetes and other diseases. This study examined whether providing calorie information on online takeaway food menus leads to lower-calorie food choices. A Menu-based Choice Experiment was conducted in November 2022 among 1040 online takeaway consumers in England (Kantar's Worldpanel Out of Home Purchase Panel). Each participant chose their preferred items from ten hypothetical menus including starters/sides, mains, desserts, and drinks. Participants were randomly allocated to a group in which the ten menus included either: a) no calorie information (group A); b) individual item calorie content (group B); or c) individual item and total calorie content (group C). An orthogonal design was used to create the menus and the probability of choosing each of the food items was estimated using a Multivariate Probit Model (MVP). There was no statistically significant difference in calories ordered by respondents in group B or group C in comparison to the control group. by. While group B and C had on average a greater likelihood of choosing low-calorie items compared to group A, the effect was only statistically significant for the low-calorie main for respondents over 55 years old in group C in comparison to the control. For these respondents, calorie information increased the probability of choosing the low-calorie main by 11.1pp ($p < 0.001$). We found no evidence that including a calorie counter had a larger impact on food choices than providing calorie information for individual items. Choices were relatively inelastic to price changes although main meals were more price sensitive (own-price elasticity −0.5 to −0.62) compared to starters, deserts and drinks (−0.22 to −0.39).

1. Introduction

Poor diet is an acknowledged major risk factor for obesity and associated non-communicable diseases worldwide. The aetiology of obesity and associated diet-related diseases is complex but the food environment is considered to play a key role in the growing prevalence of obesity (Cohen & Bhatia, 2012; Robinson et al., 2021). Eating out-of-home is linked to higher energy intake and higher body weight, which are key risk factors for obesity and diabetes (Bahadoran et al., 2015; Bezerra et al., 2012; Goffe et al., 2017; Lachat et al., 2012; Nago et al., 2014). This is because foods eaten out-of-home tend to be more processed and contain high levels of sugar, salt, saturated fat and calories compared to home-cooked meals (Cohen & Bhatia, 2012; Davies et al., 2016; Jaworowska et al., 2014; Ziauddeen et al., 2018). To encourage healthier choices, providing calorie and nutrient labelling on menus and displays in out-of-home venues has been suggested. While some policies exist that mandate calorie labelling, they typically cover only large chain restaurants (e.g. some states in the USA, Canada and

* Corresponding author.
E-mail addresses: oana.tanasache@lshtm.ac.uk (O.-A. Tanasache), t.law@reading.ac.uk (C. Law), rich.smith@exeter.ac.uk (R.D. Smith), steven.cummins@lshtm.ac.uk (S. Cummins), debekker-grob@eshpm.eur.nl (E.W. de Bekker-Grob), joffre.swait.jr@gmail.com (J. Swait), donkers@ese.eur.nl (B. Donkers), laura.cornelsen@lshtm.ac.uk (L. Cornelsen).

https://doi.org/10.1016/j.appet.2025.107894
Received 8 August 2024; Received in revised form 15 January 2025; Accepted 1 February 2025
Available online 3 February 2025

Australia) (WCRF, 2023).

In England, 'Calorie Labelling Regulations for the Out of Home Food Sector' were implemented in April 2022 (Department of Health and Social Care, 2021). This required large consumer food retail businesses (defined as those with more than 250 employees) that fell within the regulation scope to display the energy content (in kcal) of food and drinks sold and display the statement 'adults need around 2000 kcal a day'. The requirement extends to food and drink sold on a website or mobile application, including third party delivery apps. The policy is part of the drive to address high levels of obesity prevalence in England where 28% of adults live with obesity and a further 36% are overweight (NHS Digital, 2022). On average, adults in England have been estimated to consume 200–300 excess calories per day (Public Health England, 2018) while the share of household food expenditure on out-of-home consumption has steadily risen from 22% in 1995 to 31% in 2019 (Defra, 2020) giving rise to health concerns over its associated dietary risks. Research has also shown that most main meals served in major restaurant and fast-food chains in England contain more than the recommended 600 kcal energy content for a main meal (Robinson et al., 2018). One in four starters and one in five desserts individually exceed the recommended energy intake for an entire meal (Muc et al., 2019).

The effects of calorie labelling in out-of-home settings have been studied mostly in the US, and evidence consists of evaluations of the few calorie labelling mandates, real world randomized control trials in restaurants and experimental studies with hypothetical food selection tasks. Systematic reviews find mixed evidence with some concluding that calorie labelling of out-of-home foods and drinks results in either small reductions in calories ordered, ranging from −18kcal (Long et al., 2015) to −47kcal per meal (Crockett et al., 2018) while others suggesting more mixed findings (Bleich et al., 2017; Robinson et al., 2023).

The cognitive costs of tracking total calories ordered when choosing multiple items have been argued as one of the reasons behind the limited effect of calorie labelling (Gustafson & Zeballos, 2019). A study of US fast-food chains found that adult consumers underestimated the overall calorie content of meals purchased by at least 20% (Block et al., 2013). A more recent randomized experiment in a full-service restaurant, also in the US, reported that more than half of consumers underestimated the calories ordered by at least 10% (Cawley et al., 2021). The cognitive costs of tracking total calories ordered may also make the consumers prone to random errors or reliant upon simplifying heuristics such as rounding (Gustafson & Zeballos, 2019).

Few recent studies have examined the effects of providing information on the total amount of calories on food choices. Using an online hypothetical sandwich selection task, Gustafson and Zeballos (2019) found that participants provided with total calorie information ordered significantly fewer calories than those provided with calorie information for individual ingredients. In a paper by VanEpps et al. (2021) participants from a US university campus adjusted their caloric intake when provided with real-time information about the total number of calories ordered. They observed that participants presented with information on the total calorie content ordered fewer calories than those presented with calorie information on individual items only. While they were randomly allocated to different calorie labelling conditions, it is unclear whether the effect of providing information on the total amount of calories holds in more complex choice situations, such as when participants can choose more than one item from a range of foods and drinks.

This study conducted a Menu-based Choice Experiment (MBCE) to analyse the response to calorie labelling on menus featuring ten different foods and drinks. Using a controlled design, the study aimed to examine differences in total calories ordered and the probability of choosing lower calorie alternatives under three conditions: menus with no calorie information, menus with calorie information for individual food and drink items, and menus displaying both calories for individual items and total calorie content of the entire order. Additionally, the study was designed to estimate the price sensitivity for different meal components and investigate correlation in choices of individual items. Findings from this study contribute to understanding menu-based food demand and importantly, whether providing calorie information (for individual items and for the total order) encourages choice of lower-calorie alternatives and a reduction in calories ordered.

2. Methods

2.1. Experimental survey design

An MBCE was chosen for this study as it allows to analyse consumers' stated preferences systematically and consistently on menus consisting of multiple food items and allows multiple items to be chosen (Caputo & Lusk, 2022; Kilders et al., 2024). This method also mimics the ordering task that respondents would undertake in the real world, thus enhancing the external validity of experimental results (Lancsar & Swait, 2014). The study was carried out as an online survey consisting of a brief introduction to the experiment, a set of instructions on how to complete the choice tasks, ten choice tasks (menus displaying different starters/-sides, mains, desserts, and drinks) and debriefing questions.

To test the effect of providing calorie information, the sample was randomly assigned to one of three groups. All three groups received the same survey with differences only in the type of calorie information provided. For group A (control), menus displayed only the dish names and prices. Group B (treatment 1) was shown in addition the calorie information of each individual dish along with the statement 'adults need around 2000 kcal a day', as mandated by the calorie labelling regulation in England. Group C (treatment 2) received all the information shown to Group B with the addition of a calorie counter summing the total calorie content of all the dishes selected by respondents. The experimental design is summarised in Table 1 below.

2.2. Menu-Based Choice Experiment design

Each menu featured ten food and drink options: three starters or sides, three main courses, two desserts and two drinks. A 'no choice' option was provided if the respondent preferred not to choose any of the items. Respondents were asked to make a choice from the menus based on a scenario in which they are ordering the takeaway food for personal dinner consumption on a weekday. To maximise respondent engagement and account for differences across a range of foods that can be ordered online, menus were created for five cuisines (Pizza, Chinese, Indian, Burger and Fried Chicken). These cuisines were identified as the most popular takeaway choices in Great Britain (Kantar's Worldpanel Out Of Home purchase panel, online food delivery, 52w/e 17th April 2022). Appendix 1 shows an example choice menu for all three information treatments for the Pizza menu, while Appendix 2 shows the menu items used for each cuisine. We chose not to use visuals on the menu as the use of photos of dishes on menus (in physical restaurants or online) is not common in the UK (beyond large fast food chains) and may influence the respondent to make a choice based on the photo rather than the attributes of interest.

Table 1
Experimental design.

Group	Group A	Group B	Group C
Price	Market price	Market price	Market price
Information treatment		Statement 'Adults needs around 2000 kcal a day'	Statement 'Adults needs around 2000 kcal a day'
		Calorie information of each individual item is displayed.	Calorie information of each individual item *plus* a calorie counter showing total amount of calorie ordered, is displayed in real time as items are chosen.

Each of the ten food and drink options on the menu had two attributes: price and calories. Price levels were set based on information on the most popular food items purchased in Great Britain (Kantar's Worldpanel, Out of Home purchase panel, online food delivery, 52w/e 17th April 2022) and calorie content was based on information from web searches of out-of-home food providers. One option from each of the four dish types (i.e., starter/side, main, dessert, and drink) was designated as the low-calorie option. The calorie levels for the two high-calorie options within each dish (e.g., mains) were set by adding incremental amounts (e.g. 100 kcal) to the low-calorie option. For instance, if the low-calorie option was 401 kcal, the high-calorie option was 501 kcal (401 + 100 kcal). Both the low-calorie and high-calorie options are within the range of real calorie values found for similar dishes in restaurants, acknowledging the large variations in calorie content across establishments. Price and calorie levels were the same across the five cuisines, although calories were shown to groups B and C only. With four levels per attribute, the number of choice menus from a full factorial design would have been too large for an individual respondent. Thus, an orthogonal main effects design from all the possible combinations was created using the NGENE software (ChoiceMetrics, 2021). As our design had ten alternatives (i.e., food and drink options) with two attributes and four levels per attribute, the minimum number of choice menus needed was 2 × 3 (4 levels-1) x 10 = 60. We used 80 menus to ensure that we capture sufficient information and used eight blocks so that each respondent would see ten menus (see Table 2 below).

Allocation of the cuisines to each menu in the blocks was random with the restriction that each block of ten menus had to have two menus from each of the five cuisines. It should be noted that each block is not orthogonal by itself, only the combination of all blocks is orthogonal. Blocking, however ensured that attribute level balance is satisfied (ChoiceMetrics, 2021). Allocation of respondents into treatment group and block was random.

The survey was piloted in October 2022 on a sample of 113 respondents recruited from the same source as the main sample described below. The aim of the pilot was to test the clarity of the survey questions and effort in making choices. Minor adjustments were made as a result which included a) replacing one starter dish from Chinese cuisine menu to provide greater variation and b) clarifying the text of a screening and two post-experiment briefing questions.

Table 2
Attributes and attribute levels.

Food and drink options		Price	Calorie content
Starter/ side dish	Low-calorie (LC)	£1.99; £2.99; £3.99; £4.99	61 kcal, 73 kcal, 86 kcal, 98 kcal
	High-calorie (HC1)	£1.99; £2.99; £3.99; £4.99	(LC) + 150 kcal, (LC) + 250 kcal, (LC) + 350 kcal, (LC) + 450 kcal
	High-calorie (HC2)	£1.99; £2.99; £3.99; £4.99	(LC) + 150 kcal, (LC) + 250 kcal, (LC) + 350 kcal, (LC) + 450 kcal
Main dish	Low-calorie (LC)	£4.99; £7.49; £9.99; £12.49	401 kcal, 464 kcal, 526 kcal, 588 kcal
	High-calorie (HC1)	£4.99; £7.49; £9.99; £12.49	(LC) + 100 kcal, (LC) + 250 kcal, (LC) + 400 kcal, (LC) + 550 kcal
	High-calorie (HC2)	£4.99; £7.49; £9.99; £12.49	(LC) + 100 kcal, (LC) + 250 kcal, (LC) + 400 kcal, (LC) + 550 kcal
Dessert	Low-calorie (LC)	£1.99; £3.49; £4.99; £6.49	182 kcal, 238 kcal, 294 kcal, 350 kcal
	High-calorie	£1.99; £3.49; £4.99; £6.49	(LC) + 75 kcal, (LC) + 150 kcal, (LC) + 225 kcal, (LC) + 300 kcal
Drinks	Low-calorie (LC)	£0.99; £1.85; £2.65; £3.49	1 kcal; 2 kcal; 3 kcal, 4 kcal
	High-calorie	£0.99; £1.85; £2.65; £3.49	(LC) + 75 kcal, (LC) + 116 kcal, (LC) + 157 kcal, (LC) + 200 kcal

Notes: Price levels based on Kantar's Worldpanel OOH purchase panel, online food delivery, 52w/e 17th April 2022.

2.3. Participant sampling and recruitment

Our sample was drawn from the Kantar Out-Of-Home purchase panel which has about 7500 individuals in Great Britain and is nationally representative. We aimed to recruit approximately 1000 respondents (~350 respondents per group assuming population size of 7500; 95% confidence and 5% error level for a measured value within 5% of the real value). Assuming a 65% response rate, the online survey was distributed in November 2022 to approx. 1600 randomly selected participants meeting the following selection criteria: respondent was 18 years or older; resided in England; had ordered takeaway food online at least once in the past year; and was not vegetarian, vegan or on any other restricted diet. Invitations were sent via email with a personalised link to the survey. Respondents did not receive any specific compensation related to the study beyond the Kantar's standard recruitment and retention procedures. This included the receipt of reward points for providing information on their out-of-home purchases via mobile application or taking part in market research. These points can then be redeemed for shopping vouchers.

Kantar provided information on the socio-demographic profile of respondents, which are collected on an annual basis. This included occupational socio-economic status (SES) according to the National Readership Survey (AB - higher & intermediate managerial, administrative, professional occupations; C1-C2- supervisory, clerical and junior managerial, administrative and professional and - skilled manual workers, D-E – semi-skilled and unskilled manual workers, state pensioners, casual and lowest grade workers, and unemployed with state benefits only) (National Readership Survey, 2018), gender (male or female) and age (grouped into three categories - under 35 year old, 35–54, and over 55 years). Finally, to identify respondents that used calorie information (group B and C) or who would have wanted to know (group A) we used a debriefing question (see Appendix 3 for the exact wording of the question).

Ethical approval for this study was obtained from the London School of Hygiene and Tropical Medicine, UK (reference number: 27959) including study protocol. The data analysis plan was not preregistered.

2.4. Model specification and estimation

As a first step we compared calories ordered per menu overall, and for starters/sides, mains, desserts, and drinks across the three groups using a bivariate Ordinary Least Square (OLS) model where total calories ordered from a menu (overall or from starter/side, mains, desserts or drinks) were regressed against a categorical variable describing group treatment. We then added covariates of prices and calories of each of the dishes on the menu, and cuisine type. Finally, to understand sub-group effects, we included socio-demographic characteristics as categorical variables (SES, age group, and gender) in the models and their interactions with the group treatment.

As a second step, to understand if using calorie information changes choices, we compared average calories ordered overall and for starters/sides, mains, desserts and drinks within each of the three groups based on how respondents replied to the question on calorie information use (see Appendix 3 for question wording). We first ran an unadjusted model which regressed the total calories ordered against a categorical variable describing whether respondents used the calorie information (for group A the categorical variable describes whether respondents would have liked to have calorie information). We then included controls for prices and calories (group B and C only) of each dish, cuisine type and socio-demographic variables to run adjusted models.

As a third step, to understand how the provision of calorie information affected the probability of choosing items we used a Multivariate Probit Model (MVP) which accounts for possible correlation in choices. This allows, for example, the decision to order a starter to be correlated with the decision to order a main course. In the MVP model the utility of respondent i from item j is given by:

$$U_{ij} = V_{ij} + \varepsilon_{ij} = \alpha_j + \sum_k \beta'_{jk} X_{jk} + \varepsilon_{ij}$$

where V_{ij} is the deterministic part, ε_{ij} the stochastic part, of the utility function, the α_j is the alternative-specific constant, X'_{jk} in the first instance included the prices of all dishes, the calories of all dishes, dummy variables indicating group treatment and a dummy for cuisine type. As above, to understand sub-group effects, the same set of socio-demographic characteristics and their interactions with group treatment were then included. For both OLS and MVP models we present results from the models with sub-group effects included. The intermediate models with adjustment for prices, calories and cuisine type only are available from the authors.

To account for the fact that group A did not see any calorie information, calories for group A were included as zero while for group B and C calories were computed as calories seen by respondents less the average calorie for that item (i.e., deviation from the overall mean level of calories across all ten menus). For group B and C we then scaled the calorie variable using formula *X/MAX(ABS(X))*. The error vector term ε follows a multivariate normal distribution with mean 0 and a *JxJ* variance-covariance matrix sigma Σ, J the number of distinct dishes in the menu ($J = 10$ in our design). The estimation was done using the CMP command in Stata using 1009 draws (Roodman, 2007). Clustered standard errors by respondent were used in all the above-described models. To control for the false discovery rate in multiple hypothesis testing, p-values were adjusted using the Benjamini-Hochberg (BH) procedure. This adjustment was applied across all variables with reported coefficients (see Appendix 6, 7 and 9) and using an alpha level of 0.05. The BH procedure ranks p-values in ascending order and compares each to a threshold determined by multiplying the rank's position by α/m where m is the total number of tests. This ensures that the expected proportion of false positives among significant results remains controlled at the chosen alpha level.

3. Results

Table 3 below presents descriptive statistics for the sample of N = 1040 respondents which were equally distributed across the three groups. In total, 67% of the total sample invited completed the survey with 2% drop out rate for those who started the survey. There were no specific pages in the survey where respondents were more likely to drop out. The median response time was 11 min (no statistically significant difference between the three groups). In 1089 (10.5%) out of 10,400 observations (1040 respondents x 10 menus) no items were chosen (see Appendix 4 for frequency distribution). This was slightly more common in group A (control) where in 12.6% of menus nothing was chosen compared to 9.4% in groups B and C ($p < 0.001$).

As there is no population level information on the distribution of socio-demographic characteristics of online takeaway consumers we compared our sample distribution with that of the Kantar's Worldpanel Out-Of-Home purchase panel demographic estimates of the online takeaway market in England. The sample was broadly comparable to the distribution of the Kantar estimates, however we did have a slight under-representation of those younger than 35 years (10% compared to 19% on the panel), males (32% vs 49%), and those in social class D-E (15% vs 18%). Conversely, there was a slight over representation of those aged between 35 and 54 years old (57% vs 48%) and females (69% vs 52%). The groups were balanced across the socio-economic status and age. Gender showed the biggest variance with slightly more male respondents in group C.

Table 3
Descriptive statistics of the sample.

Socio-demographics (% in the population)*	Full sample (%, N = 1040)	Group A (%, N = 341)	Group B (%, N = 341)	Group C (%, N = 358)
Age				
Under 35 (19%)	10.2	9.1	10.3	11.2
35–54 (48%)	56.5	59	57.5	43.8
Over 55 (34%)	33.3	31.9	32.2	45
Gender				
Female (52%)	68.5	71.9	69.8	64.0
Male (49%)	31.5	28.2	30.2	36.0
SES				
AB (22%)	22.4	23.5	25.8	18.2
C1-C2 (61%)	62.3	61.5	60.7	64.5
D-E (18%)	15.3	15	13.5	17.3

Notes: SES was based on occupation and is based on National Readership Survey (https://nrs.co.uk/nrs-print/lifestyle-and-classification-data/social-grade/). AB=Higher & intermediate managerial, administrative, professional occupations; C1-C2=Supervisory, clerical and junior managerial, administrative and professional, and skilled manual workers, D-E = Semi-skilled and unskilled manual workers, state pensioners, casual and lowest grade workers, unemployed with state benefits only. Group A – control, group B – individual item calories, group C – individual item calories and total calories of the order. N – number of respondents in the group: *online takeaway market population in England (Kantar's Worldpanel OOH purchase panel, online food delivery, 52w/e 17th April 2022).

3.1. Calories ordered

Table 4 below shows the unadjusted calories chosen per menu for group A (control) and differences with treatment groups B and C for each dish type and in total, estimated with bivariate OLS. On average, respondents in group A chose food and drink containing 1046 kcal. Respondents who saw calorie information in both treatment groups B and C ordered slightly more calories. However, these effects were not statistically significant (at least at 5% level).

Table 5 below shows the average calories ordered by respondents in each group depending on how they replied to the question on calorie information use. Respondents in groups B and C reported similar rates of using calorie information when making choices (30% and 29%, respectively). By contrast, 40% of respondents in group A reported they would have liked to have the calorie information on the menu. Comparison of total calories ordered showed that within groups B and C those who reported using calorie information chose consistently fewer calories than those who reported not considering it. This difference was

Table 4
Unadjusted comparison of calories per respondent per menu overall and within dish type.

Group	A (SE) n = 3410 N = 341	B vs. A (SE) n = 3410 N = 341	C vs. A (SE) n = 3580 N = 358	C vs. B (SE)
Starters (kcal)	244.3 (8.0)	+17.0 (11.1)	+3.5 (10.9)	−14.4 (10.8)
Mains (kcal)	619.9 (10.8)	+22.3 (15.2)	+11.1 (14.7)	−11.2 (14.6)
Dessert (kcal)	156.5 (9.2)	+9.5 (12.9)	+12.5 (12.7)	3.0 (12.7)
Drinks (kcal)	25.8 (2.4)	+4.4 (3.6)	+2.7 (3.5)	−1.7 (3.7)
Menu total (kcal)	1046.4 (10.8)	+54.1 (14.9)*	+29.8 (14.7)	−24.3 (31.6)

Notes: includes menus where nothing was chosen (see Appendix 5 for figures where these menus were excluded) estimated via bivariate OLS with standard error (SE) clustered by respondent; group A – control, group B – individual item calories, group C – individual item calories and total calories of the order. n – number of observations in the group, N – number of respondents in the group. *$p < 0.10$, **$p < 0.05$ and ***$p < 0.01$. Authors' own analysis of Kantar's Worldpanel Panel Voice survey of 1,040 respondents, November 2022.

Table 5
Average calories per respondent per menu within group by reported use of (for B and C) or preference for (group A) calorie information.

Group	Average calories chosen (kcal)					
		Menu total (SE)	Starters (SE)	Mains (SE)	Desserts (SE)	Drinks (SE)
A n = 3410 N = 341	Would have liked to have calorie info	1079.9 (36.3)	255.7 (13.2)	639 (15.8)	162.6 (14.4)	22.7 (3.5)
	Existing info sufficient	1024.1 (30.6)	236.7 (9.9)	607.2 (14.7)	152.4 (11.9)	27.8 (3.2)
	Unadjusted difference	55.8 (47.5)	19 (16.5)	31.8 (21.6)	10.1 (18.6)	−5.2 (4.8)
	Difference (OLS adjusted)	59 (94.8)	20.12 (16)	34.3 (21.5)	10.2 (18.8)	−5.7 (4.8)
B n = 3410 N = 341	Considered calorie info	982.6 (41.2)	211.4 (12.9)	594.9 (19.4)	159.9 (11)	16.4 (3.5)
	Did not consider calorie info	1150.1 (27.1)	283.6 (9.2)	662.1 (12.7)	168.6 (16)	35.9 (3.4)
	Unadjusted difference	−167.5 (49.2)***	−72.2 (15.8)***	−67.1 (23.1)**	−8.7 (19.4)	−19.5 (4.9)***
	Difference (OLS adjusted)	−164.7 (47.4) ***	−72.3 (15.6) ***	−63.6 (22.1) **	−9 (19.5)	−19.8 (4.9) ***
C n = 3580 N = 358	Considered calorie info	986.2 (38.9)**	210.5 (8.7)	596.6 (17.6)	158.9 (14.6)	20.3 (3.8)
	Did not consider calorie info	1113.5 (25.9)	263.3 (14.2)	645.2 (11.9)	173.2 (11)	31.8 (3.2)
	Unadjusted difference	−127.3 (46.7)**	−52.8 (16.6)**	−48.6 (21.2)**	−14.3 (18.3)	−11.6 (5)**
	Difference (OLS adjusted)	−128.9 (44.9) **	−52.3 (16.1) ***	−50.7 (20.4) **	−14 (18.1)	−11.9 (5) **

Notes: includes menus where nothing was chosen, estimated via bivariate OLS (for unadjusted differences) Adjusted models estimated via multivariate OLS including price, cuisine, calories (except for group A), and socio-demographic characteristics. Standard errors (SE) were clustered by respondent; group A – control, group B – individual item calories, group C – individual item calories and total calories of the order. n – number of observations in the group, N – number of respondents in the group. *p < 0.10, **p < 0.05 and ***p < 0.01. Authors' own analysis of Kantar's Worldpanel Panel Voice survey of 1,040 respondents, November 2022.

statistically significant across all dishes, except desserts. Using the adjusted differences, those that reported using calorie information ordered 165 less kcal if in group B ($p < 0.001$) and 129 less kcal if in group C ($p < 0.05$) compared to those that did not use the calorie information. In group A, respondents who would have liked to have calorie information did not choose significantly less calories than respondents that believed the existing menu was sufficient.

Estimates of socio-demographic differences in the effect of calorie labelling on calories chosen are shown in Appendix 6. While the coefficient estimates for the interaction terms generally suggested fewer calories ordered by respondents in group C across SES and age, no evidence of a distinct pattern in calories ordered emerged between those exposed to calorie information (group B or C) and the control group after adjusting for multiple testing. Following this adjustment, only one significant interaction term remained: compared to the baseline group (females in group A), men in group C ordered more calories from drinks (23 kcal).

3.2. *Probability of choosing dishes in the whole sample*

The likelihood ratio test of independence of error terms in the MVP model was significant (Prob > χ 2 = <0.001) and thus the use of MVP was justified, indicating that the model captured wider effects than the single equation-probit model would. Fig. 1 shows the predicted choice probabilities of each menu item by treatment groups which were estimated with the MVP model including socio-demographic characteristics and interaction with group treatment effect (see Appendix 7 for full model output). As the MVP model coefficients are not directly interpretable as choice probabilities, the figure presents choice probabilities estimated via marginal effects (see Appendix 8 for table of estimates).

Fig. 1 indicates that low-calorie options were consistently less likely to be chosen compared to high-calorie options except for drinks where

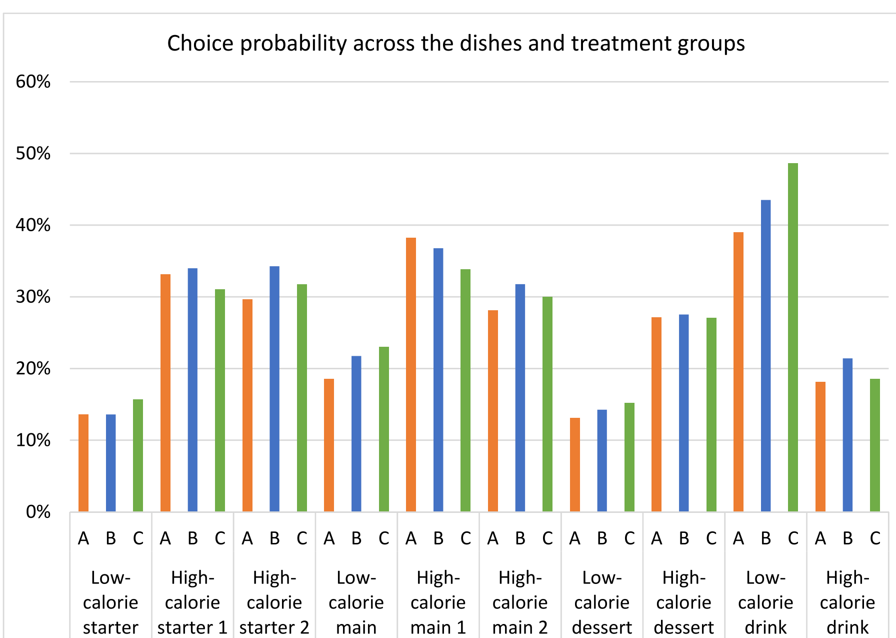

Fig. 1. Predicted choice probabilities across the 10 food and drink options and treatment groups.
Notes: group A – control, group B – treatment 1 with individual item calories, group C – treatment 2 with individual item calories and total calories of the order. Marginal effects of variables describing treatment group, estimated from MVP model controlling for prices, calories, cuisines and group interaction with socio-demographic characteristics (age, gender and occupational SES class). See Appendix 8 for the table of estimates. Authors' own analysis of Kantar's Worldpanel Panel Voice survey of 1,040 respondents, November 2022.

the opposite was observed. However, those in group C had higher likelihoods of choosing low-calorie options in comparison to the control group A. The pattern was similar in group B, with the exception of low calorie starter/sides. However, after adjusting for multiple testing, no significant differences between the three groups remained.

3.3. *Probability of choosing dishes by socio-demographic characteristics*

Fig. 2 below shows choice probabilities across the dishes for group B and C vs. group A by socio-demographic characteristics. These were estimated from the MVP model as contrasts of marginal effects of the interaction between group and socio-demographic characteristic (see Appendix 9 for detailed coefficients). The top panel of Fig. 2 shows the comparison between group B and C vs. A on the probability of choosing the low-calorie items. Those in group B and C had, on average, a greater likelihood of choosing low-calorie dishes compared to those in group A, although after multiple testing adjustment the effect was only statistically significant for over 55 years old for the low-calorie main (by 11.1pp, p < 0.001). The average likelihoods were overall more pronounced for low-calorie mains and low-calorie drinks and stronger for group C than group B.

The bottom panel showing the difference in choice probability for high-calorie dishes indicates a more heterogenous pattern with no statistically significant effects in either group B or C in comparison to

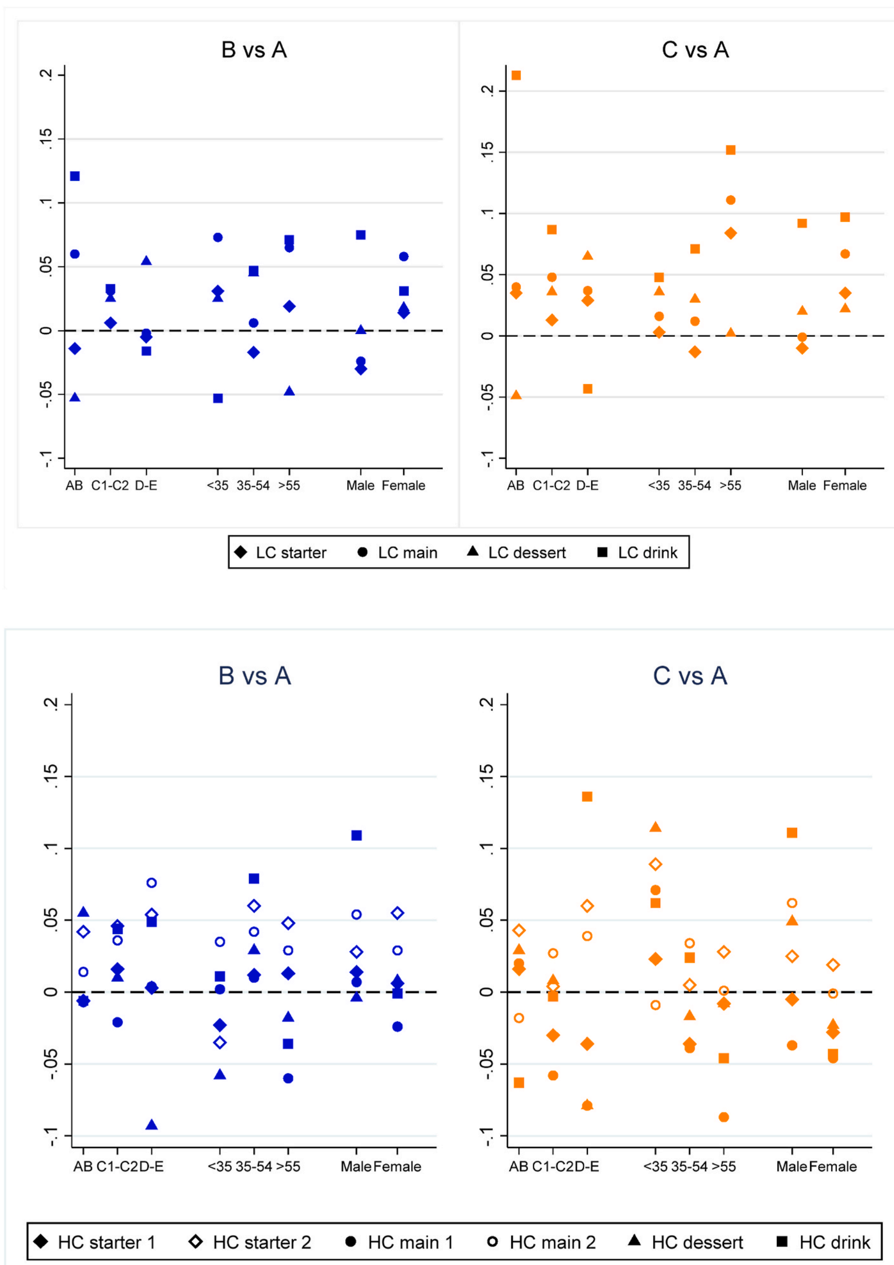

Fig. 2. Treatment effects of seeing calorie information of individual dishes (group B) and in addition total calorie content (group C) by socio-demographic characteristics on choice probability of low-calorie (top panel) and high-calorie (bottom panel) dishes.
Notes: LC – low-calorie, HC – high calorie; group A – control, group B – treatment 1 with individual item calories, group C – treatment 2 with individual item calories and total calories of the order. Contrasts of marginal effects estimated from MVP model controlling for prices, calories, cuisines and socio-demographic characteristics: age, gender, occupational SES class. Full table of estimates are presented in Appendix 9. Authors' own analysis of Kantar's Worldpanel Panel Voice survey of 1,040 respondents, November 2022.

control group A.

3.4. Responsiveness to price and calorie levels

To understand price responsiveness, we show price elasticities in Table 6 derived from the MVP model. As expected, own price elasticities were all negative and significant at least at 1% level. Choices of main dish were the most price sensitive. An increase in the price of low-calorie mains by 10% would reduce demand by 5% whereas a 10% price increase of high calorie mains reduced demand for these dishes slightly more (6.1–6.3%). Starters were less price responsive, with a 10% price increase leading to reduction in demand of 2.2%–2.9%. A bigger difference between low- and high-calorie options was seen for desserts and drinks. A 10% own price increase reduced demand for low-calorie desserts by 3.9% and for high-calorie desserts by 2.9%. Demand for low-calorie drinks reduced by 1.7% and high-calorie drinks by 3.6% with a 10% price increase.

Mains and desserts showed substitution between low- and high calorie alternatives (e.g., an increase in the price of one main dish increased the demand for other mains). We also observed some evidence for substitutions across dishes, mainly between starters and desserts and between starters and mains. For example, a 10% price increase of low-calorie desserts increased the demand for healthy starters by 1.5% ($p < 0.05$). Similarly, a 10% price increase of the high-calorie starter 2 increased the demand for the low-calorie main by 2.2%. We also saw evidence of complementarities between dishes: a 10% price increase of high-calorie desserts and high-calorie drinks decreased the demand for the high-calorie main 2 by 1% ($p < 0.01$ and $p < 0.05$ respectively).

Because calories were not seen by group A and therefore entered the model as deviation from the mean level of calories (and zero for group A) we did not calculate calorie elasticities. However, the MVP results in Appendix 7 suggest that calorie level had limited influence on choices with no clear pattern.

3.5. Correlation across choices

To get an understanding of how people may be making choices across the menu we also looked at the correlation coefficients (Table 7) from the MVP model. As expected, we found that food choices are highly correlated with most correlation coefficients significantly different from zero. All the within dish type correlations were negative and statistically significant, meaning that people were not likely to choose more than one item from the same category. For instance, the choice of low-calorie starter was negatively correlated with the choices of high-calorie starter 1 (−0.273, $p < 0.001$)) and high-calorie starter 2 (−0.194, $p < 0.001$)). Similarly, the choice of low-calorie main was negatively correlated with the choice of high-calorie main 1 (−0.392, $p < 0.001$) and 2 (−0.286, $p < 0.001$). At the same time, the choices of low-calorie dishes were positively correlated: the choice of low-calorie starter was positively correlated with choosing low-calorie main (0.245, $p < 0.001$), low-calorie dessert (0.416, $p < 0.001$) and low-calorie drink (0.176, $p < 0.001$). Similarly, choices of high-calorie dishes were more strongly correlated with other high-calorie alternatives. This implies that consumers are more likely to choose low-calorie or high-calorie dishes consistently through the menu rather than mixing for example, by choosing low-calorie starter and high-calorie main.

4. Discussion

We examined takeaway food choices and the extent to which providing calorie information encourages lower-calorie choices and reduces total calories ordered. Overall, there was no evidence that providing calorie information (either for individual items only or in combination with total calories ordered) affected calorie content of the orders overall. However, providing calorie information for individual items and for the total order (group C), increased the probability of

Table 6
Own- and cross-price elasticities.

	Low-calorie Starter		High-calorie Starter 1		High-calorie Starter 2		Low-calorie Main		High-calorie Main 1		High-calorie Main 2		Low-calorie Dessert		High-calorie Dessert		Low-calorie Drink		High-calorie Drink	
	ME	SE	ME	SE	ME	SE	ME	SE	ME	SE	ME	SE	ME	SE	ME	SE	ME	SE	ME	SE
LCS	−0.227***	0.071	0.056	0.041	0.068*	0.038	−0.073	0.057	−0.051	0.039	0.003	0.045	−0.043	0.056	0.022	0.034	−0.003	0.011	0.025	0.039
HCS1	−0.090	0.072	−0.290***	0.049	0.080*	0.043	0.088	0.058	0.008	0.041	−0.084*	0.048	−0.049	0.057	0.011	0.039	0.030	0.018	0.054	0.042
HCS2	0.081	0.069	0.078*	0.043	−0.216***	0.046	0.228***	0.058	−0.026	0.041	−0.010	0.046	0.019	0.057	−0.004	0.037	−0.007	0.014	0.001	0.042
LCM	−0.041	0.066	−0.031	0.045	0.069	0.042	−0.507***	0.070	0.058	0.041	0.246***	0.048	−0.032	0.056	−0.061*	0.037	−0.024	0.020	0.052	0.037
HCM1	−0.067	0.059	−0.059	0.041	−0.048	0.039	0.250***	0.056	−0.611***	0.051	0.449***	0.049	−0.034	0.053	−0.019	0.032	−0.037**	0.014	−0.018	0.042
HCM2	−0.106	0.072	0.026	0.042	−0.004	0.041	0.249***	0.061	0.277***	0.042	−0.624***	0.059	−0.062	0.056	−0.030	0.034	0.023*	0.012	−0.047	0.037
LCDE	0.152**	0.060	−0.025	0.036	−0.005	0.036	0.022	0.049	−0.059*	0.035	−0.004	0.038	−0.393***	0.058	0.111***	0.032	0.005	0.014	−0.034	0.030
HCDE	0.023	0.056	−0.002	0.038	−0.061	0.036	0.063	0.046	0.002	0.034	−0.107*	0.039	0.165***	0.047	−0.291***	0.035	−0.016	0.011	−0.013	0.031
LCDR	−0.035	0.054	0.008	0.037	−0.015	0.035	−0.082	0.053	0.016	0.035	0.003	0.040	−0.047	0.046	0.008	0.031	−0.171***	0.026	0.191***	0.035
HCDR	0.092*	0.051	−0.030	0.031	0.000	0.028	0.002	0.042	−0.054**	0.027	0.096**	0.032	−0.026	0.041	0.018	0.026	−0.004	0.009	−0.360***	0.043

Notes: Price elasticities are estimated as marginal effects (ME) of price coefficients from the MVP model including prices, calories, cuisine type and socio-demographic characteristics: age, gender, and occupational SES class. Shaded diagonal cells indicate own-price elasticities. Standard error clustered at respondent level. *$p < 0.10$, **$p < 0.05$ and ***$p < 0.01$.: LCS – low-calorie starter, HCS – high calorie starter, LCM – low-calorie main, HCM – high-calorie main, LCDE – low-calorie dessert, HCDE – high-calorie dessert, LCDR – low-calorie drink, HCDR – high-calorie drink. Authors' own analysis of Kantar's Worldpanel Panel Voice survey of 1,040 respondents, November 2022.

Table 7
Correlation coefficients of MVP model.

	Low-calorie Starter	High-calorie Starter 1	High-calorie Starter 2	Low-calorie Main	High-calorie Main 1	High-calorie Main 2	Low-calorie Dessert	High-calorie Dessert	Low-calorie Drink	High-calorie Drink
LCS	1									
HCS1	−0.273***	1								
HS2	−0.194***	−0.254***	1							
LCM	0.245***	−0.037	0.016	1						
HCM1	−0.018	0.162***	0.158***	−0.392***	1					
HCM2	−0.048*	0.146***	0.174***	−0.286***	−0.653***	1				
LCDE	0.416***	0.001	0.127***	0.304***	0.009	0.037	1			
HCDE	0.039	0.306***	0.280***	0.054**	0.138***	0.187***	−0.352***	1		
LCDR	0.176***	0.086***	0.172***	0.139***	0.046**	0.081***	0.395***	0.293***	1	
HCDR	0.084**	0.212***	0.137***	0.030	0.132***	0.137***	0.004	0.376***	−0.566***	1

Note: LCS – low-calorie starter, HCS – high calorie starter, LCM – low-calorie main, HCM – high-calorie main, LCDE – low-calorie dessert, HCDE – high-calorie dessert, LCDR – low-calorie drink, HCDR – high-calorie drink *p < 0.10,**p < 0.05 and ***p < 0.01. Authors' own analysis of Kantar's Worldpanel Panel Voice survey of 1,040 respondents, November 2022.

choosing a low-calorie main dish (11.1 pp) among respondents aged 55 and older.

We also found that respondents in groups B and C who reported using calorie information (29–30% in both groups) ordered significantly fewer calories overall (129–164 kcal) and across most dishes compared to those who reported not using it. In contrast, in Group A there were no significant differences between those who reported that they would have liked to have had calorie information (40%) and those who did not. This suggests that access to calorie information might be used in the desired direction by some people although we acknowledge that causality cannot be inferred due to the correlational nature of this relationship.

On average, respondents in the study full sample chose 1074 kcal per menu, which well exceeds the recommended calorie content of 600 kcal per lunch or dinner meal. This is consistent with two recent studies. A first one conducted customer intercept surveys in out-of-home eating venues in four local authorities in England and found that people ordered on average, across a range of different outlets, 1,013 kcal (Polden et al., 2023). A second, experimental study with UK adults using a virtual food delivery app also found that orders from fast-food outlets were between 1000 and 1,050 kcal (Finlay et al., 2023).

We also found that low-calorie alternatives were consistently chosen less frequently compared to high-calorie options in all three groups. This finding might suggest that takeaway is likely to be considered as a treat, as found in studies by Blow et al. (2019) and Liddiard and Hamshaw (2024). Low-calorie drinks were an exception to this, being chosen around twice as often as high-calorie drinks. This, however, is unsurprising given that these are commonly available and widely purchased in the UK market (Berger et al., 2020). Stronger correlation within low-calorie alternatives and within high-calorie alternatives than across low- and high-calorie alternatives further indicates that choices are likely to be either all low-calorie or high-calorie instead of mixing across dishes.

Our findings also align with some of the recent systematic reviews and meta-analyses on nutrition labelling in out-of-home contexts. Crockett et al. (2018) looked at the evidence of the effect of nutrition labels on menus or placed on a range of food options. They presented their findings separately for real-world settings and simulated (laboratory) settings. Their meta-analysis of the 17 studies that were, similarly to this study, conducted in simulated (laboratory) settings indicated no statistically significant impact of labelling on calories consumed. Another systematic review by Bleich et al. (2017) included 21 studies from simulated settings and concluded that results were heterogeneous with many studies of fast-food orders generally reporting no change in calories ordered while studies mimicking full-service restaurants found that calorie labels led to fewer calories ordered. Our findings also align with a recent study by Polden et al. (2024) that found no significant reduction in calories purchased or consumed in out-of-home outlets after the introduction of the calorie labelling legislation in England. However, their study was a pre-post observational study where customers were surveyed upon exiting an out-of-home outlet. No impact was also concluded in two randomized control trials of calorie labelling of alcoholic drinks. (Jones et al., 2024).

However, our findings differ from those of Finlay et al. (2023) who found that in UK adults ordered fewer calories in two out of the three studied outlet types (−19 to −54kcal from a coffee shop and fast-food outlet, respectively whereas no change was observed in orders from a sandwich shop). The main difference with this study is that Finlay et al. did not include desserts on the menus. Our findings also do not align with a recent study by Liddiard and Hamshaw (2024) who found that UK participants exposed to calorie information in a hypothetical online survey ordered less calories compared to the control group. Finally, our findings are also in contrast with those of Luick et al. (2024) who reported significant calorie reductions across several calorie label formats. Unlike our study that asked each respondent to make choices from ten different menus across five different cuisines, the studies by Liddiard and Hamshaw (2024) and Luick et al. (2024) only asked respondents to make a single choice from one menu.

Our own-price elasticity estimates indicated relatively inelastic demand with the smallest own-price elasticity estimates ranging between −0.5 and −0.63 for main meals. To our knowledge only one study in the UK has measured out-of-home food demand which found the own-price elasticity of main meals in restaurants to be −1.38 and −0.69 in fast-food outlets (Law et al., 2022). Although we did not specifically indicate which type of restaurant (fast food or not) the menus were from, our findings align with estimates for fast-food demand where prices tend to vary less and demonstrate that our findings from this experimental setting (at least regarding in price response) are comparable to those from real-life conditions. A recent menu-based choice experiment from the US also demonstrated predominantly inelastic online food delivery demand (Kilders et al., 2024). Relative demand inelasticity indicates that fiscal policies (such as taxes) may be limited in reducing the demand (and thus calories consumed) in out-of-home settings.

While a small number of existing studies (Gustafson & Zeballos, 2019; VanEpps et al., 2021) have found that providing a calorie counter of total calories ordered in the menu is effective in reducing calories ordered (by 34–105 kcal) compared to providing individual item calories alone, we did not find consistent evidence for this. We only observed that the addition of the calorie counter increased the probability of choosing the low-calorie main dish for respondents over 55 years old. One of the reasons why we found no consistent evidence could be the way the calorie counter was presented. VanEpps et al. (2021), for example, tested both numeric and traffic-light aggregation of calories and found both to be effective in reducing calories chosen in comparison to item labels only. Finkelstein et al. (2021) tested the joint impact of a healthy choice logo and a physical activity equivalent label and, similar to our study, found no effect on the overall calories chosen. Marty et al. (2021) found that providing both individual calorie and total calories in the form of a physical activity equivalent actually led to an increase in portion sizes ordered.

The study has some limitations. First, we were limited in sample size. We did not explicitly conduct sample size calculations based on effect sizes overall or in subsamples as at the time these were not available in the UK context. Retrospective power calculation using our estimates (group A mean 1046 kcal, SD 629; N = 341 (group A) and N = 358 (group C); power 0.8, alpha 0.05) indicated we would have detected an effect size of 133 kcal (approx. 7% change). Our choice scenarios were hypothetical, and respondents were not expected to follow through a choice with an actual purchase. However, the relative similarity in terms of average calories ordered compared to the study by Polden et al. (2023), along with comparable price elasticity estimates to those estimated from real-world settings (Law et al., 2022) provides confidence that these considerations did not affect food decisions. Our scenario asked the respondent to make choices for a weekday dinner for themselves. Choices made at the weekend or for the whole family may have differed from what we observe. However, including these various scenarios in the experiment were out of scope. We acknowledge that demand characteristics may have influenced respondents' engagement with the survey, as we did not include a cover story or assess participants' perceptions of the study's aims. This could have led to behaviours aligning or misaligning with perceived expectations, potentially impacting the findings. However, we believe such biases to be minimal due to the between-group design, the modest calorie information format aligned with existing labelling policies, and the possibility that participants may have believed the study was examining price sensitivities or preferences for different cuisines rather than calorie choices.

To understand responses to calorie information more completely, future research could examine how individuals process and attend to calorie information by using eye-tracking methods. By tracking eye movements during a similar choice experiment as the one reported in this article, research could examine which calorie information on the menu attracts the most attention (e.g. main course, dessert etc.; individual item calories or total calories) and shed further light into the effectiveness of different calorie information formats. Eye-tracking could also be used to examine the impact of different takeaway menu formats and calorie information placements on attention and food choices. Another alternative technique to consider is the Think Aloud method whereby participants are encouraged to talk along when completing choice tasks which provides insights into their decision-making process. For example, it is unclear how the statement 'adults need about 2000 kcal a day' is interpreted and whether it features in consumers decisions and if so, how it interacts with calorie values and numeracy skills. Also, out-of-home labelling legislations and related studies tend to focus on calories only which however does not always fully explain product healthiness or nutritional quality. Therefore, future studies could expand the labelling to provide a more comprehensive measure of the nutritional quality of the food purchased that is not solely based on the calorie content. Finally, it would be useful to understand the socio-demographic and other characteristics (e.g. health or value oriented preferences, health numeracy, motivations for takeaway consumption) of consumers who report noticing or acting upon calorie information compared to who do not.

In conclusion, we did not find evidence that providing calorie information leads to wider changes in choices or calories ordered. This might suggest that providing calorie information in a way it is currently mandated by the policy in England, is unlikely to be successful in reducing the overall calories ordered in the online takeaway context. Including information on total calories of the order (calorie counter) is also not likely to achieve this effect. The finding that most respondents did not consider any calorie information suggests that further understanding is needed on how takeaway food decisions can be influenced to improve diets.

CRediT authorship contribution statement

Oana-Adelina Tanasache: Writing – review & editing, Writing – original draft, Project administration, Formal analysis, Data curation, Conceptualization. **Cherry Law:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Formal analysis, Conceptualization. **Richard D. Smith:** Writing – review & editing, Conceptualization. **Steven Cummins:** Writing – review & editing. **Esther W. de Bekker-Grob:** Writing – review & editing, Methodology, Conceptualization. **Joffre Swait:** Writing – review & editing, Methodology, Conceptualization. **Bas Donkers:** Writing – review & editing, Methodology, Conceptualization. **Laura Cornelsen:** Writing – review & editing, Validation, Supervision, Project administration, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Data and code availability

Data can be made available on request.

Ethical statement

All procedures were performed in compliance with relevant laws and institutional guidelines. The study was approved by the London School of Hygiene and Tropical Medicine, UK (reference number: 27959).

The privacy rights of human subjects have been observed throughout the research. Informed consent was obtained from all participants prior to their participation in our study.

Funding

LC and OT were funded via UK Medical Research Council Fellowship MR/P021999/1.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Laura Cornelsen and Oana Tanasache report financial support was provided by UK Research and Innovation Medical Research Council. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Not applicable.

Appendix A. Supplementary material

Supplementary material to this article can be found online at https://doi.org/10.1016/j.appet.2025.107894.

Data availability

Data will be made available on request.

References

Bahadoran, Z., Mirmiran, P., & Azizi, F. (2015). Fast food pattern and cardiometabolic disorders: A review of current studies. *Health Promotion Perspectives, 5*(4), 231–240. https://doi.org/10.15171/hpp.2015.028

Berger, N., Cummins, S., Allen, A., Smith, R. D., & Cornelsen, L. (2020). Patterns of beverage purchases amongst British households: A latent class analysis. *PLoS Medicine, 17*(9). https://doi.org/10.1371/JOURNAL.PMED.1003245

Bezerra, I. N., Curioni, C., & Sichieri, R. (2012). Association between eating out of home and body weight. *Nutrition Reviews, 70*(2), 65–79. https://doi.org/10.1111/j.1753-4887.2011.00459.x

Bleich, S. N., Economos, C. D., Spiker, M. L., Vercammen, K. A., VanEpps, E. M., Block, J. P., Elbel, B., Story, M., & Roberto, C. A. (2017). A systematic review of calorie labeling and modified calorie labeling interventions: Impact on consumer and restaurant behavior. *Obesity, 25*(12), 2018–2044. https://doi.org/10.1002/oby.21940

Block, J.P., Condon, S.K., Kleinman, K., Mullen, J., Linakis, S., Rifas-Shiman, S., & Gillman, M.W. (2013). Consumers' estimation of calorie content at fast food restaurants: cross sectional observational study. BMJ British Medical Journal, 346. https://doi.org/10.1136/bmj.f2907 (last accessed: January 2025).

Blow, J., Patel, S., Davies, I. G., & Gregg, R. (2019). Sociocultural aspects of takeaway food consumption in a low-socioeconomic ward in Manchester: a grounded theory study. *BMJ Open, 9*(3), e023645. https://doi.org/10.1136/bmjopen-2018-023645.

Caputo, V., & Lusk, J. L. (2022). The basket-based choice experiment: A method for food demand policy analysis. *Food Policy, 109*(102252). https://doi.org/10.1016/j.foodpol.2022.102252

Cawley, J., Susskind, A. M., & Willage, B. (2021). Does information on disclosure improve consumer knowledge? Evidence from a randomized experiment of restaurant menu calorie labels. *American Journal of Health Economics, 7*(4), 427–456. https://doi.org/10.1086/714987.

ChoiceMetrics. (2021). Ngene 1.3 User manual and reference guide. https://choice-metrics.com/NgeneManual130.pdf.

Cohen, D. A., & Bhatia, R. (2012). Nutrition standards for away-from-home foods in the USA. *Obesity Reviews, 13*(7), 618–629. https://doi.org/10.1111/j.1467-789X.2012.00983.x

Crockett, R. A., King, S. E., Marteau, T. M., Prevost, A. T., Bignardi, G., Roberts, N. W., Stubbs, B., Hollands, G. J., & Jebb, S. A. (2018). Nutritional labelling for healthier food or non-alcoholic drink purchasing and consumption. *Cochrane Database of Systematic Reviews, 2018*(2). https://doi.org/10.1002/14651858.CD009315.pub2

Davies, I. G., Blackham, T., Jaworowska, A., Taylor, C., Ashton, M., & Stevenson, L. (2016). Saturated and trans-fatty acids in UK takeaway food. *International Journal of Food Sciences & Nutrition, 67*(3), 217–224. https://doi.org/10.3109/09637486.2016.1144723

Defra (2020). Family food datasets. https://www.gov.uk/government/statistics/family-food-202021 (last accessed December 2022).

Department of Health and Social Care. (2021). *Calorie labelling in the out of home sector: Implementation guidance - GOV.UK*.

Finkelstein, E. A., Doble, B., Ang, F. J. L., Wong, W. H. M., & van Dam, R. M. (2021). A randomized controlled trial testing the effects of a positive front-of-pack label with or without a physical activity equivalent label on food purchases. *Appetite, 158* (104997). https://doi.org/10.1016/j.appet.2020.104997

Goffe, L., Rushton, S., White, M., Adamson, A., & Adams, J. (2017). Relationship between mean daily energy intake and frequency of consumption of out-of-home meals in the UK National Diet and Nutrition Survey. *International Journal of Behavioral Nutrition and Physical Activity, 14*(1), 131. https://doi.org/10.1186/s12966-017-0589-5

Gustafson, C. R., & Zeballos, E. (2019). Cognitive aids and food choice: Real-time calorie counters reduce calories ordered and correct biases in calorie estimates. *Appetite, 141 (June), 104320*. https://doi.org/10.1016/j.appet.2019.104320

Jaworowska, A., Blackham, T. M., Long, R., Taylor, C., Ashton, M., Stevenson, L., & Davies, I. G. (2014). Nutritional composition of takeaway food in the UK. *Nutrition & Food Science, 44*(5), 414–430. https://doi.org/10.1108/NFS-08-2013-0093

Jones, A., Gough, T., & Robinson, E. (2024). Two online randomised controlled trials examining effects of alcohol calorie labelling on hypothetical ordering of calories from alcohol and food. *Appetite*, Article 107548.

Kilders, V., Caputo, V., & Lusk, L. J. (2024). Consumer preferences for food away from home: Dine in versus delivery. *American Journal of Agricultural Economics, 106*(2), 496–525. https://doi.org/10.1111/ajae.12428

Lachat, C., Nago, E., Verstraeten, R., Roberfroid, D., Van Camp, J., & Kolsteren, P. (2012). Eating out of home and its association with dietary intake: A systematic review of the evidence. *Obesity Reviews, 13*(4), 329–346. https://doi.org/10.1111/j.1467-789X.2011.00953.x

Lancsar, E., & Swait, J. (2014). Reconceptualising the external validity of discrete choice experiments. *PharmacoEconomics, 32*(10), 951–965. https://doi.org/10.1007/s40273-014-0181-7

Law, C., Smith, R., & Cornelsen, L. (2022). Place matters: Out-of-home demand for food and beverages in Great Britain. *Food Policy, 107*(102215). https://doi.org/10.1016/j.foodpol.2021.102215

Liddiard, E., & Hamshaw, R. J. T. (2024). 'Body dissatisfaction and beyond: Investigating attitudes towards calorie labels on UK food menus'. *Appetite, 199*(May), 107418. https://doi.org/10.1016/j.appet.2024.107418

Long, M. W., Tobias, D. K., Cradock, A. L., Batchelder, H., & Gortmaker, S. L. (2015). Systematic review and meta-analysis of the impact of restaurant menu calorie labeling. *American Journal of Public Health, 105*(5), e11–e24. https://doi.org/10.2105/AJPH.2015.302570

Luick, M., Bianchi, F., Bain, F., Bandy, L., Doshi, P., Hilliard, D., & Pechey, R. (2024). Do calorie labels change energy purchased in a simulated online food delivery platform? A multi-arm randomised controlled trial. *International Journal of Behavioral Nutrition and Physical Activity, 21*(1), 103. https://doi.org/10.1186/s12966-024-01638-y

Marty, L., Franzon, C., Jones, A., & Robinson, E. (2021). Socioeconomic position, energy labelling and portion size selection: An online study comparing calorie and physical activity calorie equivalent (PACE) labelling in UK adults. *Appetite, 166*(105437). https://doi.org/10.1016/j.appet.2021.105437

Muc, M., Jones, A., Roberts, C., Sheen, F., Haynes, A., & Robinson, E. (2019). A bit or a lot on the side? Observational study of the energy content of starters, sides and desserts in major UK restaurant chains. *BMJ Open, 9*(10), 1–7. https://doi.org/10.1136/bmjopen-2019-029679

Nago, E. S., Lachat, C. K., Dossa, R. A. M., & Kolsteren, P. W. (2014). Association of out-of-home eating with anthropometric changes: A systematic review of prospective studies. *Critical Reviews in Food Science and Nutrition, 54*(9), 1103–1116. https://doi.org/10.1080/10408398.2011.627095

National Readership Survey (2018). Social grade. https://nrs.co.uk/nrs-print/lifestyle-and-classification-data/social-grade/ (last accessed: December 2024).

NHS Digital (2022). Health survey for England 2021: Data tables. https://digital.nhs.uk/data-and-information/publications/statistical/health-survey-for-england/2022-part-2/health-survey-for-england-hse-2022-part-2-data-tables (last accessed: December 2022).

Polden, M., Jones, A., Adams, J., Bishop, T., Burgoine, T., Essman, M., Sharp, S. J., Smith, R., White, M., & Robinson, E. (2023). Kilocalorie labelling in the out-of-home sector: An observational study of business practices and consumer behaviour prior to implementation of the mandatory calorie labelling policy in England, 2022. *BMC Public Health, 23*(1), 1088. https://doi.org/10.1186/s12889-023-16033-8

Polden, M., Jones, A., Essman, M., Adams, J., Bishop, T. R., Burgoine, T., & Robinson, E. (2024). Evaluating the association between the introduction of mandatory calorie labelling and energy consumed using observational data from the out-of-home food sector in England. *Nature Human Behaviour*, 1–10.

Public Health England. (2018). Calorie reduction: The scope and ambition for action. https://www.gov.uk/government/publications/calorie-reduction-the-scope-and-ambition-for-action (last accessed: December 2022).

Robinson, E., Boyland, E., Christiansen, P., Haynos, A. F., Jones, A., Masic, U., Robertson, D., Tapper, K., & Marty, L. (2023). Is the effect of menu energy labelling on consumer behaviour equitable? A pooled analysis of twelve randomized control experiments. *Appetite, 182(November 2022), 106451*. https://doi.org/10.1016/j.appet.2023.106451

Robinson, E., Jones, A., Whitelock, V., Mead, B. R., & Haynes, A. (2018). (Over)eating out at major UK restaurant chains: Observational study of energy content of main meals. *BMJ, 363*. https://doi.org/10.1136/bmj.k4982

Robinson, E., Marty, L., Jones, A., White, M., Smith, R., & Adams, J. (2021). Will calorie labels for food and drink served outside the home improve public health? *BMJ, 372*. https://doi.org/10.1136/bmj.n40

Roodman, D. (2007). *Cmp: Stata module to implement conditional (recursive) mixed process estimator*. Boston college department of economics. VanEpps, E. M., molnar, A., downs, J. S., & loewenstein, G. (2021). Choosing the light meal: Real-time aggregation of calorie information reduces meal calories. *Journal of Marketing Research, 58*(5), 948–967. https://doi.org/10.1177/00222437211022367

WCRF (2023). Nourishing policy database. https://policydatabase.wcrf.org/level_one?page=nourishing-level-one#step2=0#step3=308. (last accessed: December 2023).

Ziauddeen, N., Page, P., Penney, T. L., Nicholson, S., Kirk, S. F., & Almiron-Roig, E. (2018). Eating at food outlets and leisure places and "on the go" is associated with less-healthy food choices than eating at home and in school in children: Cross-sectional data from the UK national diet and nutrition survey rolling program (2008–2014). *The American Journal of Clinical Nutrition, 107*(6), 992–1003. https://doi.org/10.1093/ajcn/nqy057