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Assessing the effect of health labels on online food choices

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ABSTRACT

Online takeaway platforms provide a convenient access to food and their importance has increased dramatically in the last years. Our research explores if and how food choices via takeaway apps change after individuals are informed about excessive calories, fats, carbohydrates, and salts. Our results have practical implications for public health and food choices. We designed an efficient stated choice experiment based on actual meals offered online in China and applied it in a Randomized Between-Subjects Design to a sample of 964 respondents across 10 large Chinese cities. We split the sample into two groups: exposed and not exposed to a colour-code, traffic light information system (TLS). Our analysis, using a Difference-in-Differences model and an Error Components Mixed Logit model, revealed that respondents exposed to nutrition information chose takeaway menus with less fat, salt and calories. However, the information did not affect the choice of tasty meals heavy in carbohydrates, as these are far too important in the typical Chinese diet. We also found that price, positive reviews, and delivery time were drivers of the respondents' food choices, but significantly less important than food preferences and tastiness. Regarding TLS, we confirmed that red (i.e. danger) had the most significant impact in dissuading customers from choosing unhealthy food (salt and fat). These findings are helpful in the design of public policies geared toward healthier food consumption habits in the population.

1. Introduction

Ordering takeaway food online is becoming increasingly popular everywhere, but regulations for food labelling in this case are still under development. We examine if and how a Traffic-light Labelling System (TLS) encourages consumers to make healthier choices on takeaway platforms. To our knowledge, this is the first investigation targeting takeaway consumers, using a stated choice (SC) experiment with a Randomized Between-Subjects Design. It is also the first experiment dealing with TLS in China, which is an unfamiliar way of displaying nutritional information there.

1.1. Use of food labelling

About 13 % of the world population over 17 were obese in 2016, a rate which almost tripled since 1975 (WHO, 2020). Being obese implies a higher risk of chronic diseases, such as diabetes, cardiovascular diseases, and cancer (CDC, 2024; Ng et al., 2014). Obesity has become a global public health issue and a considerable burden to healthcare systems everywhere (Bentham et al., 2017). In China, over 34 % of adults and 16 % of youngsters are obese (Pan et al., 2021). Policymakers have explored several ways to reduce obesity, such as lifestyle interventions (Webb & Wadden, 2017), public health campaigns (Kite et al., 2018) and food labelling that indicate typical values of calories, fat, saturates, and salt per serving portion or 100 g (Comans et al., 2021; Grisolía, 2018). It seems logical that better-informed consumers might choose healthier foods.

Various forms of nutrition labels are currently in use. Fig. 1 shows three commonly used types. Panel A shows guideline daily amounts, where the nutrition value is related to the daily recommended intake.

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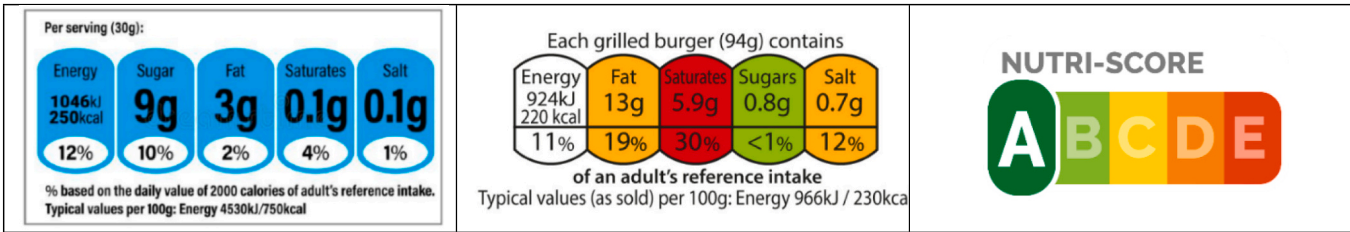


(A) Guideline Daily Amounts | (B) Traffic-Lights | (C) Nutri-score

Fig. 1. Examples of food labelling

This system evolved into the TLS, shown in Panel (B), introduced by the British Food Standards Agency[4] in 2006. TLS uses red, amber, and green colours to encourage or warn consumers about essential nutrients. Red means that people should eat less because of too much of a given ingredient, amber that people can eat most of the time, and green that the content is healthy. Finally, Panel (C) presents the Nutri-Score labelling, which summarises nutrition information, and gives one overall score. The entire scale appears on the label, with coloured letters corresponding to the product's nutritional quality enlarged (Julia & Hercberg, 2017).

1.2. Online to offline food ordering

The practice of consuming meals away from home has deep historical roots, with inns, taverns, and street vendors serving travellers and urban populations for centuries. In the United States, by the late 19th century, quick meals were commonly sold in train stations and on city streets, often by vendors from marginalized communities who turned limited resources into entrepreneurial opportunities. As cities grew and industrial work schedules prevented many from returning home for meals, the demand for convenient, affordable food increased. In the early 20th century, takeaway food became more widespread, offering portable options—from wrapped sandwiches to hot meals—that aligned with the pace of urban life. Its appeal was not only practical but economic: starting a takeaway business required relatively little capital. In many developing countries, the ongoing lack of strict regulatory oversight has further supported the expansion of informal food economies.

On the demand side, shifting family dynamics and expanding urban distances have made takeaway food an increasingly convenient option. This trend accelerated after the Second World War, driven by globalisation, the introduction of diverse culinary influences, and innovations such as phone ordering. More recently, two key developments have significantly reshaped the market: the rise of mobile applications and the COVID-19 pandemic. The pandemic prompted a surge in food delivery usage worldwide, broadening its consumer base across demographics. Meanwhile, the proliferation of mobile apps marked a disruptive shift, streamlining the ordering process and transforming the overall takeaway experience.

As consumers use mobile apps to order online and the order goes offline, it is called O2O (online to offline), a term that possibly originated in Chinese e-commerce. While traditional and online takeaway behaviours serve the same purpose, the contexts in which people make decisions differ sharply. In traditional settings, choices are often made quickly, influenced by habit, limited menus, and experience. Further, social cues - such as being with friends or interacting with staff - might play a role. On the contrary, O2O platforms create a very different decision-making environment. They offer rich visuals and detailed information that support more deliberate and exploratory behaviour. Users can browse full menus, prices, delivery times, photos, nutrition info, reviews, and promotions—all in one place. This level of detail encourages more thoughtful, attribute-based decisions rather than quick or habitual ones (Cao et al., 2011; Goffe et al., 2020). The design of these platforms also matters. Features like default options, visual highlights, and the order in which items appear can subtly push users toward certain choices (Wang et al., 2022). The private nature of online ordering may also lead people to indulge more since no one is watching (Miura et al., 2012). Thus, O2O platforms create a different decision-making space altogether. This shift suggests that pro-health interventions such as TLS might work differently online.

Given these differences and the rapidly expanding use of O2O platforms, it becomes even more important to examine how nutrition-related interventions function within this digital environment. Indeed, there has been a dramatic increase in the O2O takeaway market for food and beverages worldwide (see, Duthie et al., 2023). For instance, over 970 million O2O users ordered online takeaways in 2021, and revenue in the online food delivery segment reached nearly US$ 315 million in 2022, most of it in China (Statista, 2021). *Just Eat PLC*, a leading O2O takeaway platform present in 23 countries, has a gross merchandise value (GMV) of nearly US$ 14 billion, featuring about 590 million consumer orders in 2020 (Just Eat, 2020). In addition, in the first half of 2019, the GMV of the Chinese takeaway market alone was over US$ 89 billion (IResearch, 2020), a growth of 39.3 % compared to 2018. Finally, O2O takeaway apps created a boom for the fast-food businesses in China, because customers could access fast food without location issues. Although O2O takeaway apps are used daily by consumers, little is known about how they shape and inform the dietary choices or how they affect the health of users.

Ordering takeaways using O2O apps may lead to unhealthy food choices. Jaworowska et al. (2014) examined the nutritional content of 489 meals from 274 takeaway establishments in the UK, finding that most meals were inconsistent with UK dietary recommendations. Zhao et al. (2015) collected food consumption data from 1981 adults and 971 children in Beijing, reporting that average dietary salt intake significantly exceeded the amount recommended by the World Health Organization (WHO). They also found that 43 % of salt intake among urban working-age individuals came from food prepared in restaurants. Similarly, Miura et al. (2012) reported that regular users of O2O takeaway services had higher body mass indices (BMI), particularly among socioeconomically disadvantaged groups.

1.3. Nutrition labels and TLS

There is also a growing interest with understanding and identifying the use and effectiveness of nutrition labels expected to influence people's food choices, nudging them toward healthier alternatives (Azman & Sahak, 2014; Roberto & Khandpur, 2014; Robertson et al., 2023). However, some consumers feel that the information provided is too complicated and hard to understand; further, they find it challenging to balance their consumption of the various nutrients; finally, some

[4] The Food Standards Agency (FSA) is responsible for food safety and hygiene in England, Wales, and Northern Ireland. https://www.gov.uk/government/organisations/food-standards-agency

consumers zero in on only one nutritional value, often focusing on fat or calories, ignoring the rest (Gallicano et al., 2012).

Nevertheless, there is evidence that labelling might be a valuable tool to assist consumers. Talati et al. (2017) conducted a comparative experiment across 12 countries, finding that TLS and Nutri-score were the most effective front-of-pack labelling (FOP) on foods. Hagmann & Siegrist (2020) demonstrated that TLS produced better results than the Nutri-score. TLS has been tested also in experimental and field studies, showing positive results (Lima et al., 2019). Fichera & von Hinke (2020) investigated FOP labelling, presenting the amount of energy, saturated fat, sugar, and sodium in a quasi-experiment. They used a Difference-in-Differences model with actual purchase data, finding that FOP improved the nutritional quality of purchases. Some studies have also identified the effect of TLS on different products. For example, Stamos et al. (2019) found that although TLS reduced the consumption of sugary drinks it did not work with food.

A recent analysis across 18 countries found that FOP nutrition labels were effective in guiding healthier food choices. Specifically, consumers preferred products with favourable nutritional profiles when such information was clearly displayed (Julia et al., 2025). Similarly, Braesco & Drewnowski (2023) reported that FOP labels significantly influenced consumer behaviour by increasing the selection of healthier options; these labels helped consumers make quicker and more informed choices, particularly when shopping time was limited. Furthermore, Varela et al., (2024) reviewed evidence on the role of food packaging, including labels, on children's diets, concluding that labels could positively affect children's dietary choices by highlighting healthier options, aiding parents and children in selecting nutritious foods. Sousa et al. (2023) examined Brazilian consumers' intentions to use food labels finding a high level of intention to use them for making healthier food choices. On the other hand, Sun et al. (2024) highlighted the broader public health implications of dietary behaviours influenced by food labels, arguing that clear and accessible health information on labels could lead to improved dietary habits and a reduced incidence of diet-related diseases such as diabetes.

In summary, recent studies collectively demonstrate the positive influence of food labelling on people's dietary choices.

1.4. Using a stated choice experiment

A Stated Choice Experiment (SCE) is well-suited for this study, as it allows for the *ex-ante* evaluation of policy effects on food choices. This application is especially relevant for assessing TLS, which has not yet been applied in the O2O context. A SCE breaks down choices into measurable attributes—such as nutritional labels, price, delivery time, and taste—making it possible to analyse consumers' trade-offs. This feature helps policymakers understand how people weigh health information like TLS against other factors such as tastiness or convenience (Train, 2009; Ortúzar & Willumsen, 2024). The format also reflects the O2O environment, where decisions are made based on visual and detailed information. Moreover, discrete choice models—particularly Mixed Logit—capture taste heterogeneity and allow the replication of complex substitution patterns more effectively than more straightforward methods. A SCE also allows for controlled attribute variation, generating richer insights than real-world data alone. Finally, it enables the estimation of marginal willingness to pay (WTP) for service and nutritional features, which is difficult to achieve with revealed preference data.

Many studies have used choice experiments to analyse food choices (Grisolía et al., 2012; Huang et al., 2020; Livingstone et al., 2021; Paffarini et al., 2021; Palma et al., 2018; Wang et al., 2018). Some have specifically applied SCE to assess the impact of nutrition information on consumer decisions (Ballco et al., 2019; Erdem, 2022; Peschel et al., 2019). However, while these studies examine nutrition information on packaging or restaurant menus, none have explored how such information on online takeaway platforms influences consumer choices using discrete choice models.

1.5. Research questions

As we have seen, there is an expanding body of literature demonstrating that TLS can influence consumer food choices in traditional retail and in-person dining environments (Hersey et al.,2013; Hawley et al., 2013). However, its effectiveness in O2O food purchasing platforms remains untested. Online platforms engage different psychological processes—such as more intentional browsing, access to detailed product information, and visual customization—that may affect how labelling strategies work. Given the rapid growth of the O2O food delivery market, assessing whether TLS remains effective in this context is both timely and important. It also aligns with public health efforts to improve dietary choices through digital interventions. This leads to the first research question:

RQ1: Does TLS make people choose healthier options in the online ordering context?

While the general principle behind TLS is well-documented, the psychological and behavioural salience of its colour codes in digital settings remains under-explored. Prior studies have largely treated TLS as a monolithic intervention, rather than disentangling the distinct persuasive effects of individual colours (see, for instance, Aschemann-Witzel et al., 2013). In digital environments—where interface design and visual attention patterns differ markedly from physical retail, the relative impact of each colour could vary significantly, but no systematic study has established this hierarchy in an O2O context.

Identifying which TLS elements drive the most behavioural change would enable more precise tailoring of digital labelling systems to maximize public health impact. Thus, the second research question is formulated:

RQ2: Which TLS colours are most effective in influencing healthier food choices online?

Lastly, while TLS can support healthier choices, it competes with other key factors in online food ordering, such as price, delivery time, peer reviews, and perceived taste. As shown in in-store experiments, even strongly favourable attitudes toward healthy food can be overridden by more immediate or familiar cues (Sigurdsson et al., 2011; Talati et al., 2016). However, few studies have ranked these factors to show how TLS fits into the broader decision-making process. This leads to the third research question:

RQ3: Which factors matter most when people order food online?

Answering these three questions offers a comprehensive framework to evaluate the real-world viability of TLS in digital food environments and provides evidence-based design implications for platform developers and public health policymakers alike.

Our aim was to examine how TLS influences consumers in making food choices. We collected data using an SC experiment with a Randomized Between-Subjects Design to determine the impact of TLS on food choices in an O2O takeaway context. The remainder of the paper is structured as follows. Section two presents the methodology, survey design and data collection; section three presents our main model results and section four discusses our conclusions.

2. Methodology and data

2.1. Stated choice experiments

The basic underpinning of SC experiments is random utility theory (Ortúzar & Willumsen, 2024; Train, 2009). Its simplest formulation considers that the utility U_{njt} associated with alternative j (belonging to a set of J available alternatives; in our case, each one is a different meal), for individual n in choice situation t, is divided – for modelling purposes – into a deterministic vector V_{njt} and an error component $\mathscr{E}_{njt}$ (which appears because the modeller is not aware of all the attributes considered by the individuals when making choices), such that:

$$U_{njt} = V_{njt} + \mathscr{E}_{njt} \tag{1}$$

where V_{njt}, the representative utility, is typically specified as the weighted sum of a set of K characteristics or attributes, x_{njt}, multiplied by fixed parameters β_{jk}, to be estimated:

$$V_{njt} = \sum_{k=1}^{K} \beta_{jk} x_{njt} \tag{2}$$

and different models can be generated depending on assumptions about the error terms.

For example, if the error terms distribute independently and identically (i.e. with the same variance) across alternatives following an Extreme Value Type I distribution and we have only one choice situation per individual (as in revealed preference studies), we get a Multinomial Logit (MNL) model, where the probability of choosing alternative i has the following form (McFadden, 1974):

$$P_{ni} = \frac{\exp(\lambda V_{ni})}{\sum_{j=1}^{J} \exp(\lambda V_{nj})} \tag{3}$$

where λ is a scale factor inversely related to the unknown standard deviation of the errors $\mathscr{E}$, which cannot be estimated separately from the coefficients $\boldsymbol{\beta}$ in eq. (2).

However, the MNL is limited and unrealistic. First, it assumes that alternatives are independent and that there is no heterogeneity (i.e., the errors have the same variance). Second, as it has fixed parameters, it assumes all individuals have the same taste. This can be partially addressed by introducing *systematic taste variations*, that is, allowing the model parameters to vary with certain socioeconomic variables (Ortúzar & Willumsen, 2024; page 290). Instead, the state of practice Mixed Logit (ML) model, allows for random taste variations among individuals, unrestricted substitution patterns between alternatives, choice heterogeneity and even correlation in unobserved factors over time (Train, 2009).

Here, we estimated an Error Components Model (ECM), a form of the ML model with the following utility function:

$$U_{nj} = \delta_i + \alpha x_{nj} + u_n z_{nj} + \varepsilon_{nj} \tag{4}$$

where δ_i is an alternative specific constant (ASC); x_{nj} and z_{nj} are vectors of measurable attributes relating to alternative j; $\boldsymbol{\alpha}$ is a vector of fixed coefficients to be estimated; $\boldsymbol{u}$ is a vector of random terms with zero mean; and ε_{nj} is, again, an iid Extreme Value Type I error term. The elements z_{nj} are error components that together with ε_{nj} define the stochastic portion of utility across different individuals.

From this utility form, to calculate the willingnes-to-pay (WTP) in a model with linear representative utilities as (2), we have to compute the ratio of the coefficient of the k^{th} attribute and that of the estimated parameter of *price* (Daly et al., 2023). This is the ratio of two marginal utilities where the price parameter is a proxy for the marginal utility of income (Sillano & Ortúzar, 2005):

$$WTP_k = \frac{\beta_k}{\beta_{price}} \tag{5}$$

2.2. Difference-in-differences (DiD) modelling

Following a Randomized Between-Subjects Design, we allocated individuals randomly to one of two groups: (i) the *treatment group*, receiving the intervention under study and (ii) the *control group*, receiving the conventional treatment (Kendall, 2003). To check for differences in outcome between individuals in both groups, they were followed up making sure that their only difference was the intervention they received.

We used a DiD approach to estimate the outcome (Gibson & Zimmerman, 2021). Our treatment group consisted of respondents exposed to TLS information (the control group did not receive it). A DiD approach needs a 'common shock assumption', which held here since TLS had yet to be applied in China. It also assumes parallel trends in the pre-treatment outcomes for both groups. There are reasons to support this assumption in our study:

1. All respondents in both groups were recruited from the same ten cities and had been active takeaway users in the last six months.
2. Respondents in both groups were of similar age.
3. The parallel outcome trends were seen in both groups before the TLS information was confirmed, as we will show below.

Our DiD model compared the consumers' intake of calories, fats, carbohydrates, and salt in both groups. For this, we posited the following general equation:

$$Y_{nd} = \gamma_0 + \gamma_1 Survey_n + \gamma_2 Card_d + \gamma_3 Survey_n Card_d + \gamma_4 S_n + \tau_{nd} \tag{6}$$

where Y_{nd} represents the calorific, fat, carbohydrate, and salt intake by individual n in choice scenario d. The dummy variables *Survey* and *Card* equalled one if the individual belonged to the treatment group and the choice scenario contained TLS information, respectively. $\boldsymbol{S}$ denotes a vector of sociodemographic variables, and $\boldsymbol{\tau}$ is a vector of error terms; the parameters $\boldsymbol{\gamma}$ are to be estimated. Our results are presented in section 3, incorporating also the effects of socioeconomic and other variables that might influence the results.

2.3. Stated choice (SC) survey design

We designed a SC experiment with 24 choice scenarios and four alternatives, including a non-purchase-option[5] (NPO). We created different questionnaires for the treatment and control groups following a Randomized Between-Subjects Design. Individuals in the control group faced a questionnaire without any labelling information (TLS) across all choice scenarios. Participants in the treatment group faced a questionnaire where the first 12 choice scenarios were identical to those of the control group, and the second 12 contained TLS information. Previously, they received a neutral introduction explaining how to interpret TLS (see Fig. 2). As the meals presented were identical in both questionnaires and followed the same order, the only difference between the information received by both groups was the TLS presented in scenarios 13 to 24.

We selected respondents between 18 and 40. We excluded individuals on a diet or following dietary restrictions achieving a sample of 1075 subjects who entered the randomization process. Afterwards, 111 individuals were removed, as shown in Fig. 2, because they showed lexicographic preferences or provided incomplete responses.

2.4. Attributes and levels

Prior to designing the SC experiment, we conducted six focus groups to help defining an initial set of attributes. Then, three pilot studies allowed us to discard non-significant attributes and improve the questionnaire. Finally, we selected the following attributes: price, reviews, delivery time, and taste (type of meal), with the levels shown in Table 1.

To make the experiment as realistic as possible, we analysed the top sales meals of the two most popular O2O takeaway platforms in China, *E'lema* and *Meituan*, selecting 48 meals. We did not include just familiar meal items, as TLS might have less effect because of the inertia in their eating habits. However, we used the same meal list in both surveys for

[5] This is important when individuals face alternatives where none of which might be found acceptable, as forcing them to choose one in that case might trigger a different response mechanism (Olsen & Swait, 1998).

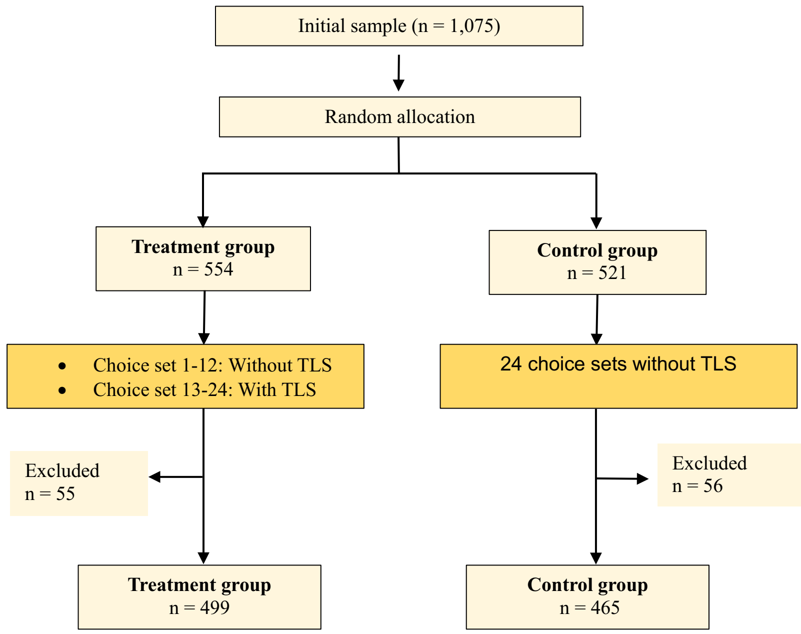


Fig. 2. Flow diagram of the experiment.

Table 1
Attributes and levels.

Attributes	Levels
Price (RMB)	15, 20, 25, 30, 35, 40, 45, 50, 55
Reviews (stars)	2, 3, 4, 5
Delivery time (min)	30, 35, 40, 45
Taste (type of meal)	very light, light, heavy, very heavy

consistency and comparability.

Concerning *price*, we analysed hundreds of meals finding that heavier meals were usually more expensive than light orders. Thus, for realism, we created a design where *price* and *type of meal* were correlated. Notwithstanding, this correlation was built into blocks where we allowed for price variability within the same type of meal. We considered the most frequent price range to show the general takeaway cost. To add diversity, we also included the four most expensive food items.

Reviews represented the meal's quality and were displayed using 'star ratings' ranging from two to five, with five stars indicating the highest quality. We excluded one-star ratings for the sake of realism, as the O2O platforms in China do not list any restaurants with such low ratings. *Delivery time* had four levels, ranging from 30 to 45 min, which reflects a realistic range for O2O takeaway platforms in China.

Regarding *taste* or *type of meal*, we were aware that personal preferences and tastes can strongly influence food choices (Garcia-Bailo et al., 2009), which complicates the analysis due to its correlation with calorie content. This attribute was designed to capture the appeal of tastiness independently from the appeal of healthiness, which was represented by a TLS dominated by green colours. This separation allowed us to avoid, to a certain extent, the potential negative bias associated with the red colour. To address this, we classified meals into four categories: very light, light, heavy, and very heavy, using light as the reference level. In the questionnaire, these levels were presented using a 'number of thumbs' scale. We also categorized calories into four levels: very light (<122 Kcal), light (127–173 Kcal), heavy (180–235 Kcal), and very heavy (239–323 Kcal). Nutritional information for each meal was obtained from the Bohe Nutrient app. Fig. 3 illustrates this process.

Table 2 displays the list of meals used alongside the TLS information including calories, fats, carbohydrates, and salt. However, some meals were treated as special cases, considering the amount of salt and fat, as well as different cooking techniques (see Table 3). The colour associated with each nutrient was determined with reference to the UK Food Standards Agency (see details in Table 4).

2.5. *Drawing a meal*

For each type of meal in the experimental design, we took a draw from Table 2. For example, if the corresponding category was light for a specific alternative, we randomly selected an item from that category (i.e., from numbers 25 to 36). Once a meal was chosen, we used its description in terms of calories, salt, fat, and carbohydrates in the questionnaire.

2.5.1. *Experimental design*

We applied a D-efficient design using Ngene (ChoiceMetrics, 2014) to produce the final questionnaire. Before, we conducted one pre-test and three pilot studies with different sample sizes of 20, 40, 20, and 20 individuals. We applied an orthogonal design for the pre-test based

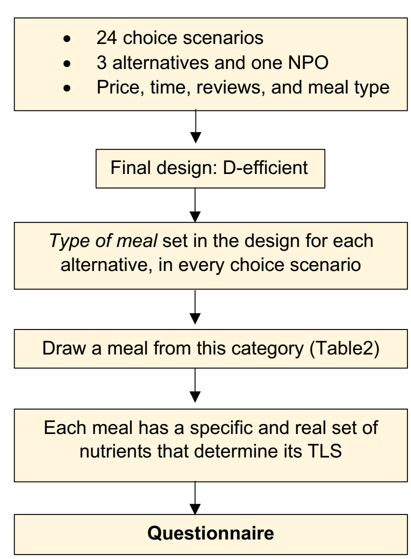


Fig. 3. Selecting meals for the final questionnaire

Table 2
List of meals.

No.	Meal type	Name	Calorie (Kcal)	Fat (g)	Carbohydrate (g)	Salt (g)
1		Pizza	314	19	27	0.254
2		Fried chicken strips	239	18	2	0.207
3		Spring rolls with fried chicken	247	19	10	0.321
4		Rice topped with fried chicken	210	9	26	0.264
5		Spicy soup with meat and vegetables	348	27	17	0.83
6		Spicy chicken leg burger	320	17	28	0.729
7		Bacon burger	311	19	19	0.729
8		Fried chicken legs	279	17	11	0.755
9		Pork dumplings	253	17	22	0.350
10		Pasta	379	5	233	0.105
11		Chinese hamburger (Roujiamo)	290	8	36	0.678
12	Very heavy	Seafood rice noodles	323	12	47	3.241
13		Fried shredded pork with rice	224	12	14	0.547
14		Spicy chicken legs with rice	228	7	33	0.035
15		Pork steak with rice	187	5	28	0.298
16		Fried pork dumplings	235	13	23	0.468
17		Roast duck with rice	276	18	26	0.446
18		Vegetarian fried rice noodles	219	7	35	0.902
19		Bibimbap (spicy meat and veg in a bowl)	194	8	25	0.521
20		Braised pork rice with peas	224	13	19	0.498
21		Rice with sweet and sour pork ribs	197	8	25	0.446
22		Hot pot with chicken wings and rice	180	7	25	0.386
23		Hainan chicken with rice	209	7	25	0.987
24	Heavy	Turkish barbecue with rice	181	7	25	0.648
25		Mouthwatering chicken with rice	160	9	4	0.285
26		Meat and vegetable rice noodle soup	92	4	12	0.450
27		Fried tomato with eggs and rice	136	7	20	0.116
28		Cold noodles with green pepper and shredded pork	128	2	23	0.396
29		Kung Pao chicken with rice	127	7	7	0.568
30		Spicy lobster	87	4	1	0.357
31		Fried rice noodles with vegetables and pineapple	173	9	19	0.361
32		Fried rice cake	118	4	21	0.173
33		Curry pork steak with rice	128	5	17	0.249
34		Barbecued pork with rice	160	4	25	0.276
35	Light	Braised pork steak with scallion and rice	170	5	25	0.479
36		Rice topped with tomato, potato and eggs	143	6	19	0.182
37		Dumpling soup	217	8	28	0.451
38		Congee with preserved eggs	63	1	12	0.234
39		Corn and egg vegetable salad	87	4	11	0.181
40		Cucumber Sushi	74	0.3	16	0.151
41		Cold noodles with veg in vinegar	109	4	15	0.391
42		Corn kernels	96	2	14	0.016
43		Seafood noodles	94	0.4	20	0.045
44		Hot and sour shredded potato with rice	122	6	14	0.366
45		Rice noodles with hot and sour vegetable soup	98	4	15	1.278
46		Shredded chicken with cold noodles	129	3	20	0.339
47		Vietnamese beef soup with rice noodles	74	1	12	0.052
48	Very light	Eight types of grains and beans Congee	76	4	9	0.020

on seven attributes and levels defined by the focus groups and literature review. The successive pilots allowed us to reduce the number of attributes following the guidelines of Caussade et al. (2005).

In each round, we followed this flow of actions: (i) conduct the survey; (ii) collect responses; (iii) estimate a model; (iv) discard non-significant parameters; (v) use the parameters estimated in the model as priors for a new D-efficient design. Fig. 4 shows examples of choice scenarios. In the case of the treatment group, respondents were first introduced to TLS and then presented with a series of scenarios, as shown in Panel (A). The control group participants faced scenarios like the one in Panel (B). In both cases, the choice question was: "Assuming this order is for your lunch, which meal would you choose?"

2.6. Data collection

We designed two online surveys and implemented them in Qualtrics. The survey company (Sojump Data Collection) randomly collected responses from 10 large cities in China (Beijing, Shanghai, Guangzhou, Chengdu, Chongqing, Wuhan, Suzhou, Hangzhou, Nanjing and Shenzhen). Together, they represented 85 % of the market of O2O takeaway platforms and takeaway users aged 18 to 40 in 2020 in China (IResearch, 2020). The company maintains panels of respondents who agree to take online surveys for a compensation. We asked for samples where the participants were from 18 to 40 and had ordered O2O takeaways in the last six months.

Table 5 shows that there are no significant differences between the control and treatment groups in terms of the respondents' demographic profile.

3. Results

3.1. DiD model results

We organized this section in two parts. First, we explore descriptive trends using graphical evidence. Then, we present the formal estimation results of the DiD model using regression analysis.

Table 3
Classification of special meals.

No.	Meal type	Name	Calorie (Kcal)	Fat (g)	Carbo (g)	Salt (g)	Special cases' reason
4	Very heavy	Rice topped with fried chicken	210	9	26	0.264	Deep fried dish
17	Heavy	Roast duck with rice	276	18	26	0.446	Roasting, relatively less salt
30		Spicy lobster	87	4	1	0.357	Relatively more salt
26	Light	Meat and vegetable rice noodle soup	92	4	12	0.450	Relatively more salt
32		Fried rice cake	118	4	21	0.173	Deep fried dish
37	Very light	Dumpling soup	217	8	28	0.451	Relatively more salt
46		Shredded chicken with cold noodles	129	3	20	0.339	Relatively less fat

Table 4
Criteria for nutrition contents.

	Low	Medium	High	
Colour code	Green	Amber	Red >12.5 % of RIs	>15 % of RIs
	Per 100 g	Per 100 g	Per 100 g	Per portion
Fat	3.0 g or less	3.0–17.5 g	More than 17.5 g	More than 21 g
Carbohydrates	5.0 g or less	5.0–22.5 g	More than 22.5 g	More than 27 g
Salt	0.3 g or less	0.3–1.5 g	More than 1.5 g	More than 1.8 g

Note: The portion size criteria apply to portions/serving sizes greater than 100 g. RIs refer to dietary reference intakes.
Source: Food Standards Agency (2016).

3.2. Descriptive trends and graphical evidence

We examined the parallel trend assumption (Gibson & Zimmerman, 2021) for all dependent variables in the DiD data. Calories, fat, carbohydrates, and salt refer to the average content on each card selected. Thus, the assumption tested was whether the content of the four dependent variables revealed similar trends between the treatment and control groups.

From cards 13 to 24, the fat/cal/salt graph shows significant changes between the treatment and control groups. Average fat, calories and salt had a lower intake in the treatment group than in the control group. More specifically, choice cards 13, 16, 18 and 21 show a sharp reduction in fat, calories, and salt intake for the treatment group.

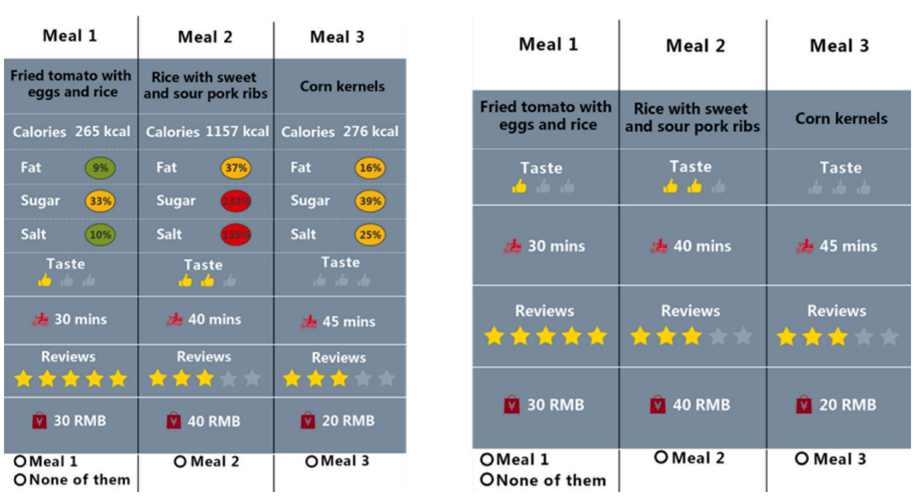
Fig. 5 shows similar trends between treatment and control participants from cards 1 to 12 (i.e., those that were the same) for the four nutrients; this is consistent with the parallel trend assumption required by the DiD approach. The graph provides a visual representation of the experimental design, where the treatment group receives TLS information only from card 13 onwards, while the control group continues under identical conditions. This structure allows us to isolate the causal effect of TLS by comparing changes in average nutritional intake over time between the two groups; this effect will be estimated more formally below.

Note that the four choice cards included at least one very heavy meal. For example, cards 13, 16 and 21 included hamburgers or fried chicken, labelled high-fat and high-calorie meals in our meal list. So, the confirmed reduction of average fat and calories implies that TLS can indeed help participants to avoid ordering unhealthy meals. In addition, cards 18 and 21 included two hefty meals (e.g., hamburger and hot pot) labelled as high-salt, and fewer participants chose these dishes when the TLS information was displayed.

Interestingly, carbohydrates showed fewer changes between the treatment and control groups. Cards 13 and 18 had a higher carbohydrate intake in the treatment group than in the control group, which may be caused by the desire to avoid a high-fat intake in the same choice scenarios; this outcome was confirmed by the results of the discrete choice models as we will see below. For example, card 13 had a high-fat alternative meal and a high-carbohydrates alternative meal. Card 18 included a high-fat alternative meal and two high-carbohydrate alternative meals.

4. Results

Table 6 shows the main DiD results for the odds of fat, salt, carbohydrate, and calorie intake. Regression models were estimated using STATA 17.0, based on 16,666 observations. Each model in Table 6 uses the same explanatory variables but a different nutritional outcome as the dependent variable: fat (Model 1), salt (Model 2), carbohydrates (Model 3), and calories (Model 4).



(A) Scenario for treatment group (B) Scenario for control group

Fig. 4. Example of stated choice scenario.

Table 5
Summary of sample demographic characteristics.

Socioeconomic variable	Level	Treatment group % of total (n = 499)	Control group % of total (n = 465)
Age	18–23	27.7	23.8
	24–29	31.1	28.2
	30–35	26.1	32.2
	36–40	15.2	15.8
Gender	Male	45.9	55.9
Income (RNB)	<3000	20.8	16.7
	3000–5000	14.4	19.1
	5001–7000	19.4	18.8
	7001–9000	19.8	21.3
	9001 and above	25.5	24.2
Education	Less than high school	5.6	7.7
	Bachelor's degree	82	81
	Master's degree	10.8	10
	Doctoral degree	1.2	1.1
	Others	0.4	0.2
Frequency of ordering takeaway food	Every day	9.1	9.3
	More than 3 times a week	50.7	53.1
	Once a week	28.8	28.8
	Once a month	9.3	7.8
	Other	2.1	1.1
Diet control	Yes	57	48.8
	No	43	51.2
Favourite type of food	Chinese food	69.8	63.6
	Western food	2.9	1.7
	Both	27.4	34.7
Employment status	Yes	77.1	82.3

TLS is represented by a dummy variable that equals one for participants in the treatment group and for choice scenarios where the TLS information was shown. This effect is captured by the interaction term γ_3 in eq. (5), which reflects the impact of TLS on individuals' intake for each of the four selected nutritional elements.

Note that the treatment effect is negative and significant for fat (Model 1). Indeed, the model shows that participants tend to choose meals with lower fat content after being exposed to nutritional label information. However, the negative treatment effects for calories (Model 4) and salt (Model 2) are not statistically significant. While respondents tended to order fewer calories and less salt when TLS was present, these reductions were not significant.

Conversely, the treatment effect for carbohydrates is positive and significant, suggesting that TLS did not deter participants from choosing meals higher in carbohydrate content. One possible explanation is that participants actively avoided meals high in fat—prompted by the TLS warnings—and, in doing so, selected meals with relatively higher carbohydrate content as a compensatory response. This pattern may reflect a form of nutritional substitution: because fat is more energy-dense than carbohydrates (9 kcal vs. 4 kcal per gram), reducing fat intake may lead consumers to increase their intake of carbohydrates to maintain satiety or perceived portion size. This could explain also why fat intake decreased significantly while carbohydrate intake increased. A similar substitution for salt is not necessary, as salt contributes no calories and has only a minimal effect on portion size. The estimated effect on calories was negative, though only significant at the 75 % confidence interval. As for salt, the treatment effect was negative but not statistically significant—possibly due to Chinese consumers' preference for salty tastes and long-standing dietary habits (Zhao et al., 2015).

The *Policy* variable captures general changes in meal selection between the first and second halves of the choice tasks (i.e., before and after choice set 13), independent of TLS exposure. Across the four models, we observe significant effects: a positive shift in fat, carbohydrates, and calories and a negative shift in salt intake. These patterns may reflect learning effects, changes in attention or fatigue, or differences in the nutritional profile of meals presented in later sets. Importantly, the coefficient of *Policy* reflects temporal trends common to both treatment and control groups and is not attributable to the TLS intervention itself.

Group holds for individuals assigned to the treatment group, regardless of whether the scenarios included TLS or not. This parameter shows that participants in the treatment group had slightly different food preferences even before the TLS was introduced—selecting meals with less fat and more carbohydrates than those in the control group. Nonetheless, these differences are accounted for in the model, and the treatment effect is interpreted as a relative change from this baseline.

Regarding the control variables, more frequent takeaway users (who order takeaways more than three times per week) and female takeaway users reduced their calories and carbohydrate intakes after exposure to TLS. Compared with takeaway users without a favourite diet, those with a favourite diet chose fewer calories and carbohydrates when exposed to TLS. Finally, dieters selected foods higher in fat and lower in carbohydrates compared to non-dieters, and participants over 30 reduced their salt intake after seeing the TLS.

4.1. Discrete choice experiment

4.1.1. Model estimation results

Several Error Components (EC) mixed logit models were estimated using Apollo (Hess & Palma, 2019). Because we collected data from two groups—one exposed to the TLS attribute and one not—for joint estimation it was necessary to assess whether both datasets shared the same variance in the unobserved part of utility. This is done by estimating the ratio of the scale factors associated with modelling with each dataset independently, as described in Ortúzar and Willumsen (2024, section 8.7.3). The estimated scale factor ratio was 1.03 and not significantly different from 1, indicating that the error variance across the two datasets was statistically equivalent. Thus, although the treatment group was exposed to one additional attribute (TLS) in choice sets 13–24, the similarity in scale suggests that respondents processed the choice tasks consistently across groups. This supports the validity of our experimental design and ensures that differences in choice behaviour can be attributed to the TLS intervention rather than differences in error variance.

The utility function of the best model specification had the following form:

$$\begin{aligned}U_j = &\sum_{m=1}^{M}\beta_m{}' + \beta_{ASCj} + \beta_{time}{}^*time + \beta_{reviews}{}^*reviews + \beta_{price}{}^*price\\ &+\beta_{fat-green}{}^*(\delta_{fg}{}^*fat) + \beta_{fat-red}{}^*(\delta_{fr}{}^*fat) + \beta_{carb-y}{}^*(\delta_{sy}{}^*carbo)\\ &+\beta_{carb-red}{}^*(\delta_{sr}{}^*carbo) + \beta_{salt-green}{}^*(\delta_{sag}{}^*salt) + \beta_{salt-y}{}^*(\delta_{say}{}^*salt)\\ &+\beta_{salt-red}{}^*(\delta_{sar}{}^*salt) + \beta_{cal}{}^*calories + \beta_{light}{}^*(light + v - light)\\ &+\beta_{heavy}{}^*Heavy + \beta_{vheavy}{}^*vHeavy + \beta_{fat_{r_{old}}}{}^*(\delta_{old}{}^*\delta_{fr}{}^*fat)\\ &+\beta_{fat_{r_{fem}}}{}^*(\delta_{fem}{}^*\delta_{fr}{}^*fat) + \boldsymbol{\sigma_{panel}}\end{aligned} \tag{6}$$

where the attributes used are defined in Table 7, which also shows the estimation results for our best model.

One of the determinants of food choices is taste (Catellani & Carfora, 2023). We aimed to capture it by attaching a specific constant to each meal, represented as β_m in eq. (6). Initially, the experiment included 48 of these constants, but we merged coefficients with the same value and discarded those that were non-significantly different from zero, ending with 27 constants. These are large and significant, revealing the importance of the uniqueness of the product aside from other attributes such as price or nutritional value. For example, the coefficient for meal 7 (bacon burger) is 3.021 (t = 21.98), whereas that for meal 20 (Braised pork rice with peas) has a significant negative value of −1.623 (t = −12.04), showing the large variation in preferences across meals.

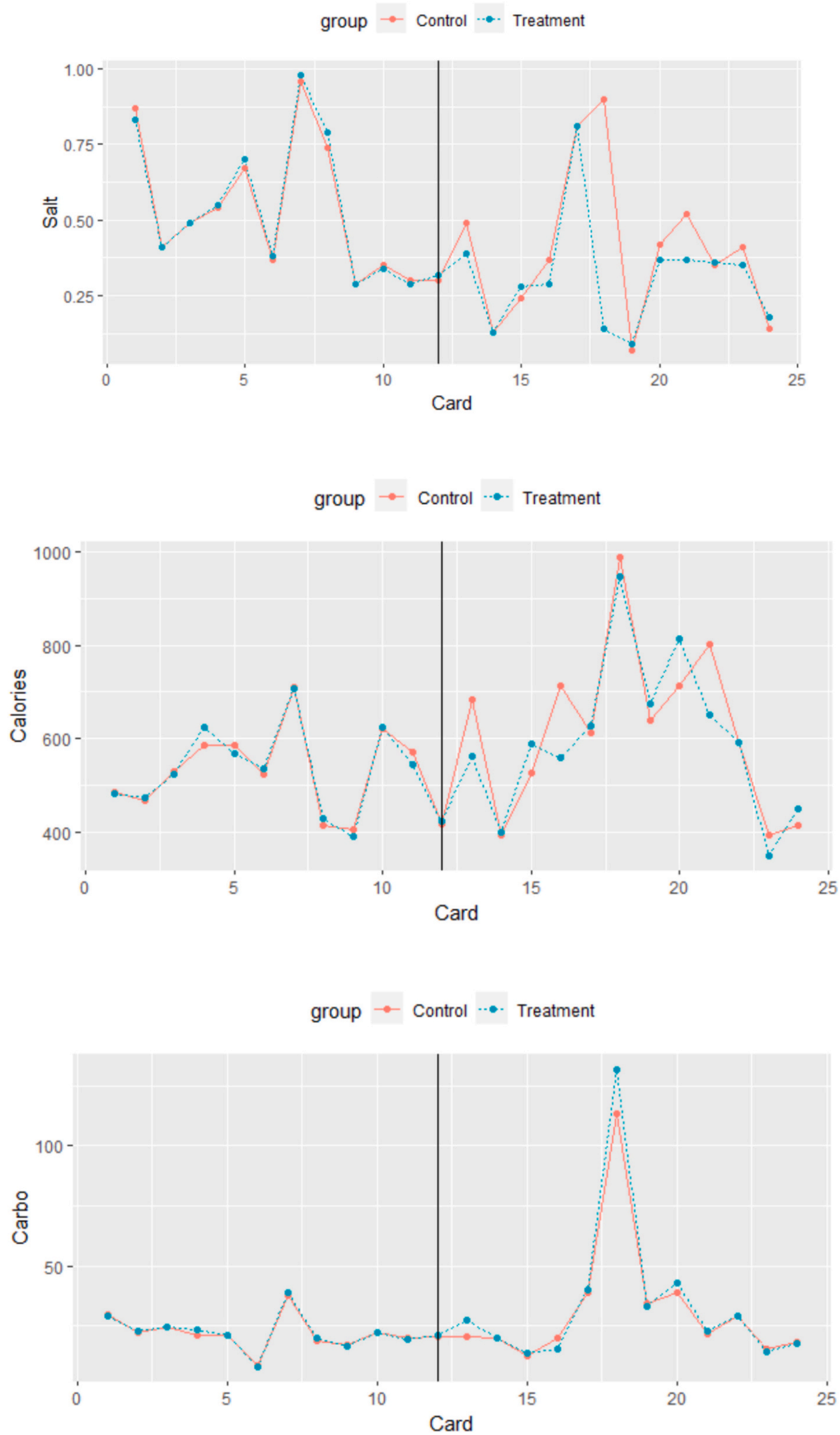


Fig. 5. Treatment effects on average fat/carbohydrate/salt/cal intake per card.

The concept of taste preference is also reinforced by the attribute *tastiness* (*type of meal*): light, heavy, and very heavy. Table 6 shows that heavy meals are preferred over light or very light meals, with a coefficient of 0.305 ($t = 5.59$). In turn, very heavy meals have three times the impact, with a coefficient of 1.038 ($t = 18.78$). This differentiation was intended to reflect how tasty these dishes are. On the other hand, the meal constants attached to specific meals captured the distinctiveness of each dish and its connection to individual preferences, which, as we observe, play a crucial role.

In addition to the constants for meals, we also estimated ASC

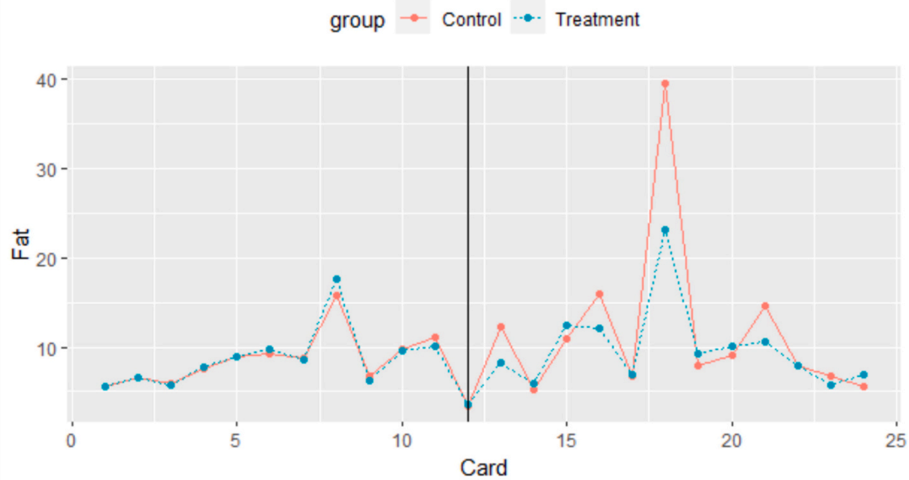


Fig. 5. (*continued*).

Table 6
Differences in differences model results.

	Model 1: Fat		Model 2: Salt		Model 3: Carbohydrate		Model 4: Calories	
Dependent variables	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
TLS effect	−0.04 ***	-5.24	−0.01	-0.94	0.02 ***	3.86	−0.01	-1.28
Policy	0.11***	14.98	−0.15 ***	−20.29	0.17 ***	28.17	0.20 ***	30.52
Group	−0.03***	-4.93	0.00	0.39	0.03 ***	4.59	−0.01	-1.26
Over 30	−0.01 **	-2.00	−0.02 ***	-2.63	0.01	0.93	0.00	-0.78
High frequency	0.00	0.16	0.02 **	2.23	−0.01**	-2.41	−0.01 **	-2.30
Female	−0.01 *	-1.88	0.00	0.72	−0.01 **	-2.03	−0.02***	-2.89
Favourite food	0.00	-0.06	−0.01	-0.78	−0.01 **	-2.22	−0.01 *	-1.81
Control diet	0.02 ***	2.71	−0.01	-1.00	−0.01 **	-2.09	0.00	-0.20
No. of observations	16,666		16,666		16,666		16,666	
Adjusted R^2	0.01		0.02		0.03		0.04	

Note: $***p < 0.001$, $**p < 0.05$, $*p < 0.1$, all for two-sided tests.

attached to each alternative, representing their location in the choice card (left, middle, and right), and considered the NPO as the reference alternative. The results show that the alternative displayed in the middle has a disadvantage compared to the rest, including the NPO. The middle position has a significant negative coefficient of −0.929 ($t = -13.23$). This position bias has been found before (Hensher et al., 2015) and suggests that consumers are more likely to remember the first and last items in lists compared to middle items.

The coefficients associated with the service attributes—*delivery time*, *reviews*, and *price*—are all significant and with the expected sign. In particular, delivery time has a negative coefficient of −0.006 ($t = -3.76$), which is in line with findings by Gunden et al. (2020). The coefficient for reviews is 0.034 ($t = 2.18$), indicating that each additional star increases utility; this coefficient also shows that reviews are the most valued among the service attributes. This aligns with previous findings in online shopping contexts (Cao et al., 2011; Engler et al., 2015), possibly reflecting an attempt by consumer's to reduce uncertainty in this type of decision-making.

Next come the relevant variables related to TLS and calories. In relation to salt, carbohydrates, and fat, recall that the experiment showed percentages of recommended daily intake and a colour code. We combined both, treating colour as a dummy variable and percentage as that displayed in the choice cards. Thus, δfg, for example, is a dummy that takes the value one when fat is displayed as green and it is multiplied by the percentage in fat. The same structure is followed for the rest of the nutrients. Notice that, potentially, we could have nine parameters of this sort, but we found that only seven were significantly different from zero.

Most signs were as expected: for instance, green salt had a strong positive effect (0.085, $t = 14.55$), while red salt was negative (−0.066, $t = -12.53$). The exception was carbohydrate-red, which was significant but positive (0.004, $t = 6.21$).[6] In fact, for carbohydrates, only the red version was significant, though with this contrary sign—albeit consistent with the results of the DID approach. On the other hand, the estimated coefficient for red-fat is −0.012 ($t = -7.19$), significant and with the expected sign, which is in line with the findings of Emrich et al. (2017), that TLS reduces the intake of total fat.

Aside from the TLS results, the experiment also showed that the amount of calories had a negative impact, with a coefficient of −0.003 ($t = -12.37$). Although calories can be seen as something negative, they could also be perceived positively, as they are often associated with more filling or tastier meals (Grisolía et al., 2013). We attempted to capture this 'tastiness' with the classification explained before, finding significant and positive dummies for very heavy and heavy meals in relation to the light and very light meals. This indicates that more tasty meals are also more popular. We can observe that the coefficients increase as we move from very light to heavy and very heavy meals. For instance, the size of the parameter of a very heavy meal (1.038) is over three times that of a heavy one (0.305).

4.1.2. *Heterogeneity*

We examined heterogeneity by allowing interactions between the

[6] This can be due central role of staples like rice, noodles, dumplings, and steamed buns in Chinese diets, as we discuss below.

Table 7
EC model estimates.

Attribute	Name	Explanation	Estimate	Rob. t-rat.
Constants	b_Extreme position	Extreme left or right	0.005	0.68
	b_Middle position	Middle position	−0.929	−13.23
	NPO (reference)	Non-purchase-option	–	–
Service attributes	b_time	Delivery time	−0.006	−3.76
	b_reviews	Reviews (one star)	0.034	2.18
	b_price	Price	−0.030	−14.39
Fat	b_fat_green	Green	0.021	9.49
	b_fat_red	Red	−0.012	−7.19
Carbohydrate	b_carbo_red	Red	0.004	6.21
Salt	b_salt_green	Green	0.085	14.55
	b_salt_ye	Yellow	−0.045	−10.25
	b_salt_red	Red	−0.066	−12.53
Calories	b_cal	1 kcal	−0.003	−12.37
Tastiness (type of meal)	b_light (reference)	Light and very light	–	–
	b_heavy	Heavy meal	0.305	5.59
	b_vheavy	Very heavy meal	1.038	18.78
SE interactions	b_fat_red_old	Fat red * elderly	−0.003	−2.29
	b_fat_red_fem	Fat red * female	−0.003	−2.15
Sigma panel	Standard deviation panel effect error component		0.792	25.78
Meals	b_meal2_19	Fried chicken strips-Bibimbap	0.580	7.91
	b_meal5	Spicy soup with meat and vegetables	1.066	12.64
	b_meal6	Spicy chicken leg burger	0.403	4.76
	b_meal7	Bacon burger	3.021	21.98
	b_meal8	Fried chicken legs	0.187	1.94
	b_meal9_22	Pork dumplings- Hot pot with chicken	0.832	16.60
	b_meal10	Pasta	1.532	14.47
	b_meal14	Spicy chicken legs with rice	1.726	23.43
	b_meal15_43	Pork steak with rice-Seafood noodles	0.566	9.00
	b_meal17	Roast duck with rice	1.362	19.33
	b_meal18	Vegetarian fried rice noodles	0.708	12.40
	b_meal20	Braised pork rice with peas	−1.623	−12.04
	b_meal21	Rice with sweet and sour pork ribs	1.264	15.21
	b_meal25_31	Mouthwatering chicken with rice-Fried rice	0.191	3.96
	b_meal27	Fried tomato with eggs and rice	2.285	21.27
	b_meal28	Cold noodles with green pepper and shredded pork	2.342	25.78
	b_meal29	Kung Pao chicken with rice	0.200	2.09
	b_meal32	Fried rice cake	1.351	9.78
	b_meal33	Curry pork steak with rice	1.510	14.30
	b_meal34_36	Barbecued pork with rice-rice topped with tomato	1.202	16.77
	b_meal35	Braised pork steak with scallion and rice	0.650	5.12
	b_meal38	Congee with preserved eggs	1.260	11.46
	b_meal39	Corn and egg vegetable salad	−0.369	−4.95
	b_meal40	Cucumber Sushi	0.161	1.91
	b_meal41	Cold noodles with veg in vinegar	1.162	10.00
	b_meal42	Corn kernels	1.752	16.99
	b_meal44	Hot and sour shredded potato with rice	1.359	14.74
Final log likelihood		−27,849.2		
Log-likelihood market shares model		−30,953.5		
AIC		55,784.4		
BIC		56,130.5		

various attributes and the individuals' socioeconomic characteristics to capture systematic differences in preferences (Ortúzar & Willumsen, 2024, page 290). Two interactions stood out: being female and being closer to 40. Both significantly increased the negative response to the red labels associeted with high fat content. These findings are consistent with previous research showing that women are generally more responsive to health labels, especially those using interpretive colour cues like red, which often signals danger or prohibition (Meng & Chan, 2022; Koenigstorfer et al., 2014). This heightened sensitivity may reflect greater health risk perception, stronger involvement in food choices for themselves and their families (Song et al., 2021), and more concern with fat intake due to body image or health motivations (Kunz et al. 2020).

Similarly, older individuals (closer to 40) may react more strongly to red fat labels due to increased health awareness and risk aversion, particularly regarding chronic diseases like cardiovascular conditions (Scarborough et al., 2015). They also tend to rely more on heuristic cues, making colour-coded warnings more salient than numeric data. Thus, this group is more likely to interpret fat warnings as immediate health risks (Trudel et al., 2015). In essence, while the average effects of the traffic light labels were modest, these subgroups showed significantly stronger reactions to the red fat labels, reflecting how colour cues may interact with individual health priorities.

Another source of heterogeneity is the importance of the specific constants attached to the 27 meals mentioned earlier. Although these constants are not linked to any particular group, they likely reflect variation in individual tastes across the sample and their influence on food choices.

A final manifestation of heterogeneity was captured by *sigma*, the standard deviation of the normally distributed error component, which was added to account for the pseudo panel structure of our dataset. In our case, the estimated value of *sigma* was highly significant ($t = 25.78$), highlighting its role in capturing unobserved individual-specific factors that systematically influence choices across repeated tasks. Unlike the heterogeneity explained by observed interactions (e.g., gender or age) or the fixed preferences inferred from meal-specific constants, *sigma* reflects a latent, residual preference correlation—the kind of consistency in individual behaviour that remains even when all observable attributes are controlled for. This intra-individual correlation implies that some respondents consistently prefer certain types of meals or exhibit systematic avoidance behaviours that are not explained by the measured attributes. Thus, incorporating *sigma* into the model enhances its behavioural realism and statistical robustness. Ignoring such panel effects would not only bias the standard errors but also mask important underlying preference structures. Accounting for this source of heterogeneity is especially crucial in stated choice experiments with repeated observations (Cherchi & Ortúzar, 2011).

4.1.3. *Willingness to pay (WTP)*

We applied eq. (7), using the Delta Method available in Apollo (Hess & Palma, 2019), yielding the values shown in Table 8.

The WTP for an additional reviews' rating star is 1.13 RMB

Table 8
Willingness to pay.

WTP	Unit	RMB	US$	t-ratio
Reviews	One star	1.13	0.16	2.36
Delivery Time	One minute	0.18	0.03	3.41
Fat Green		0.09	0.01	8.23
Salt Green		2.85	0.40	11.52
Fat Red	One percentage point	0.39	0.05	6.71
Carbohydrate Red		0.12	0.02	5.63
Salt Yellow		1.52	0.21	−9.50
Salt Red		2.22	0.31	−10.48
Calories	1000 Kcal	8.60	1.20	9.80
Heavy meal		10.25	1.44	7.03
Very heavy meal		34.96	4.89	23.41

(approximately 0.16 US$) per meal. The WTP for reducing one minute of delivery time is 0.18 RMB (ie., 10.8 RMB/h). This is equivalent to 1/3 of the average hourly wage in Chinese urban areas (i.e., 33.6 RMB/h in 2020[7]).

Among the six key TLS attributes, the highest WTP are for the salt component. For example, the WTP for reducing it in one percentage point is US$ 0.31 in the case of red and US$ 0.21 for yellow. Further, our results suggest that individuals would be willing to pay US$ 0.4 to increase the green colour one percentage point. In the case of fat, the figures are much smaller, and the same occurs with carbohydrates.

On the other hand, participants appear to be willing to pay approximately US$ 1.2 to reduce 1000 Kcal in their dishes (ceteris paribus). Finally, the WTP for heavy and very heavy meals represent a payment for the entire meal, as a premium compared to light or very light meals, which is almost US$ 4.9 and 1.4, respectively. Therefore, participants appear to be willing to choose tasty meals despite their negative aspects (calories, fat, and carbohydrates).

5. Discussion

In this section we will discuss our results as a response to the research questions set at the start.

RQ1: Does TLS make people choose healthier options in the online ordering context?

Our findings indicate that TLS influences food choices, except in the case of carbohydrates. This likely reflects the central role of staples like rice, noodles, dumplings, and steamed buns in Chinese diets. These carbohydrate-rich foods are consumed daily and are explicitly promoted by China's national dietary guidelines as the foundation of a grain-based diet (Chinese Nutrition Society, 2022). Chinese cultural norms further reinforce the necessity of such staples, as meals are considered incomplete without them (Ma, 2015). Indeed, carbohydrates are viewed as essential sources of energy and satiety, deeply embedded in routine eating habits and cultural familiarity, making consumers inherently less sensitive to health label warnings for carbohydrates than for nutrients such as fat or salt (Song et al., 2021; Zhang et al., 2020).

The literature on this topic does not offer a clear consensus. In general, studies support the idea that TLS encourages healthier choices, as demonstrated across different methods and contexts (e.g., Defago et al., 2020; Osman & Thornton, 2019; Sonnenberg et al., 2013). However, no studies have specifically examined its application in the online food ordering context, particularly through mobile apps. This aspect is crucial, as the proportion of food purchased through this channel is substantial in China and continues to grow exponentially worldwide. The decision-making process in mobile app ordering differs significantly from traditional settings and, therefore, requires more specific policy considerations.

RQ2: Which colours are most effective?

In terms of colours, Fig. 6 below displays the marginal utilities of each colour, representing the impact of a one-percentage-point change on utility. Green has a positive impact, while red is the most deterrent, and noticeably, the effect is more pronounced for salt than for fat.

It is unsurprising that red is the most effective colour in dissuading people from unhealthy options. Red is commonly associated with danger, warnings, and stopping, which naturally makes consumers more hesitant to select those items. Magnetic resonance imaging (MRI) studies have shown that red labels activate brain regions linked to response inhibition, making consumers more likely to avoid unhealthy foods (Zhang et al., 2020). Additionally, presenting red in contrast with green further reinforces this reaction.

The impact of red has been consistently observed in natural field experiments (Thorndike et al., 2014), experimental analyses (Marette et al., 2019), online surveys (Marette et al., 2021), and choice experiments (Balcombe et al., 2010; Scarborough et al., 2015).

What about green? As expected, our experiment confirms that green positively influences purchase decisions. The effect of green nutritional labels has been documented before. Green labels can lead consumers to perceive food products as healthier, even when their nutritional content is identical to items labelled with other colours (Ducrot et al., 2016; Schuldt, 2013; Vasiljevic et al., 2015). In our experiment, green was slightly more influential than red. Excluding carbohydrates, for fat and especially salt, both red and green had a significant impact, as Ducrot et al. (2016) noted … '*Red and green might be particularly useful because of their automatic association with stop and go*'.

Recall that, aside from colours, our experiment also included the calories of each meal as part of the nutritional information. Calories were displayed just below each meal. Their impact on the model was very significant and counted in Kcal, overrode the influence of colours. Unlike the case of TLS, previous research does not show a strong support of calories to nudge people toward healthy foods. Evidence is mixed. Systematic reviews show a mixed result with impact only in some cases (see for instance Bleich et al., 2017). In restaurants, calorie labels can lead to a reduction in calories ordered, with some studies showing a decrease of up to 18.13 Kcal per meal (Cecchini & Warin, 2016). However, the impact is often small and varies significantly across studies (Cantu-Jungles et al., 2017). In a natural field experiment, the calories displayed had a modest impact (Cawley et al., 2020). In general, calories might have influence in specific groups of people or types of food. As such, calorie labelling can lead to healthier food choices particularly among overweight individuals (Lim et al., 2018), those who are on a diet (Girz et al., 2012) and the impact is more pronounced in women than in men (Gerend, 2009). Overall, calorie labelling can influence food choices, but its effectiveness is often limited and context dependent.

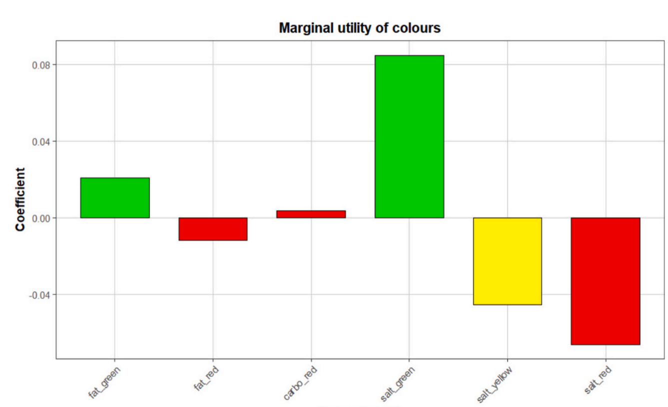


Fig. 6. Marginal utility of each colour in TLS.

[7] The National Bureau of Statistics in China does not publish hourly wage figures. However, based on published data for 2020 on annual wages in the private and non-private urban sectors, as well as workforce headcounts in each sector, we calculated a weighted annual average wage for urban workers of 81,320 RMB.

The integration of TLS labelling into mobile food ordering applications may not be practical due to the limited screen space on mobile devices. Introducing complex nutritional information could clutter the interface, potentially increasing order errors and longer processing times, thereby diminishing the user experience and efficiency (Wang et al., 2022). Moreover, unlike TLS, caloric information does not require prior knowledge or training to interpret. It is presented as a single numerical value, occupying significantly less space on the display. This simplicity and clarity suggest that calories might be a more suitable alternative for mobile food ordering applications. However, research indicates that caloric information alone is insufficient. Menu labelling with calorie counts has a limited impact on reducing calorie intake. Yet, when combined with contextual or interpretive information (e.g., daily intake recommendations or TLS), it can lead to a more significant reduction in calorie consumption (Cawley et al., 2020; Sinclair et al., 2014).

RQ3: Which aspects are most important for online food purchases?

Let us consider all factors that influence food choices aside from TLS and calories. These include service attributes such as price, delivery time, and customer reviews, as well as tastiness, which we classified into three categories (dummies representing less tasty dishes). Additionally, there are 27 significant constants attached to specific meals. Service attributes were measured in units, whereas tastiness and meal-specific constants are categorical variables (dummies). As a result, a direct comparison between them is not advisable. However, trade-offs can still be observed. For instance, a meal with a 5-star review rating increases utility by 0.16, which would be offset by a price increase of 6 RMB, equivalent to an additional 30 min of delivery waiting time.

Conversely, the impact of tastiness and the constants attached to specific meals is more significant. There are 15 meals with a specific constant above 10, indicating a strong consumer interest in those dishes. As such, we must emphasize that the main driver of food choice in this experiment was personal preferences. Although this driver has long been recognized in the food science literature, food choices are also influenced by other factors, such as budget, context, mood, tradition, and availability.

Considering both cooking methods and ingredients, this subgroup of 15 popular meals can be divided into two categories: *Carb-based* meals and *Light and refreshing* meals. The first group considers meat-heavy, saucy dishes with rice, typically braised or stir-fried, resulting in a deep, umami-rich flavour. Examples include curry pork steak with rice, barbecued pork with rice, fried tomato with eggs and rice, and roast duck with rice. The second group comprises milder, lighter dishes, often boiled, steamed, or served cold, emphasizing freshness and balance. Examples include congee with preserved eggs, cold noodles with vegetables in vinegar, corn kernels, and hot and sour shredded potato with rice.

In addition, this experiment demonstrates the significant role of tastiness in food choices. Indeed, if the meals mentioned above belonged to the 'very tasty' category, they would increase marginal utility by 10.37. Tastiness has been widely recognized as a key driver of food choices, as demonstrated in numerous studies (Brug et al., 2008; Nicklaus et al., 2004; Rozin, 2015). People are naturally drawn to foods high in sugar, fat, and salt due to our evolutionary survival mechanisms (Galindo et al., 2012).

To summarize, the most influential factors in food choice are personal preferences, followed by tastiness. While service attributes (such as price, reviews, and delivery time) are essential, they do not compare to the strength of tastiness and personal preferences when selecting food through online apps.

6. Conclusions

We conducted a stated choice experiment on a large sample of people residing in several Chinese cities, using actual meals offered by popular Chinese takeaway firms. We applied both an error components mixed logit model and a differences in differences approach to analyse the influence of several elements (including a traffic light system, TLS) on respondents' online takeaway food choices. To the best of our knowledge, this is the first study to examine the impact of nutritional labels in the mobile app market.

Our findings indicate that TLS can shape consumer behaviour, particularly by reducing fat consumption, but it appears to have little to no effect on carbohydrate selection. While prior research generally supports the effectiveness of TLS in nudging consumers toward healthier choices, its impact in mobile ordering contexts was understudied. Given the rapid growth of online food delivery in China and worldwide, understanding these dynamics is critical for future policy design. Additionally, a randomized between-subjects design allowed us to confirm that individuals were more likely to choose healthier options when TLS labeling was present. In particular, we found that fat intake significantly decreased compared to the control group. Regarding colour-coded labels, our results confirmed that red was the most effective deterrent, particularly for salt, while green encouraged healthier selections. The contrast between red and green strengthens this effect, consistent with previous research on automatic stop-and-go associations.

Our experiment also highlighted the importance of service attributes in food choices. Participants were willing to pay 1.3 RMB per star in customer reviews, confirming reviews as the most influential service attribute. In terms of TLS, willingness to pay (WTP) was highest for salt, with individuals willing to pay around 2 RMB to reduce one red colour point. They were also willing to pay nearly 9 RMB to reduce a single Kcal in their meal. However, personal preferences and tastiness remained the strongest drivers of food choice in our experiment. Meals classified as 'very tasty' significantly increased consumer utility, overriding other considerations. Furthermore, the model highlighted the exceptional importance of 15 specific meals, which we grouped into carb-based meals and lighter-refreshing meals. Ultimately, our findings emphasize that while TLS and calorie labels can influence food choices, taste and personal preferences remain the primary determinants in mobile food ordering.

Our study further contributes to the existing literature by using a realistic setting, selecting real meals from actual online platforms rather than synthetic scenarios, as is common in stated preference experiments on food choices. As a further consideration to improve realism of the experiment, TLS information was extracted from these meals, ensuring that all attribute levels were familiar to respondents.

CRediT authorship contribution statement

Anna Wang: Writing – original draft, Visualization, Validation, Software, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Jose M. Grisolía:** Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ada H.Y. Ma:** Writing – review & editing, Supervision, Software, Formal analysis, Conceptualization. **Juan de Dios Ortúzar:** Writing – review & editing, Supervision.

Ethical statement

Ethical statement We confirm that this manuscript has not been published or presented elsewhere in part or in entirety and is not under consideration by another journal. All study participants provided informed consent, and the study design was approved by the appropriate ethics review board of the University of Nottingham Ningbo on April 13th 2019. We have read and understood journal's policies, and we believe that neither the manuscript nor the study violates any of these. There are no conflicts of interest to declare. The lead author has full access to the data reported in the manuscript. This data is available on request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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