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Can traffic light labelling nudge heuristical decision processes?

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Abstract
This research investigates the effect of different front-of-pack nutritional labelling on individuals' decision-making processes and food choices. To do this, we combine a stated choice experiment, a preference elicitation technique, with an eye-tracking experiment to explore the tendency to make fast (or slow) decision-making processes. Our results show that when the tendency to make fast decisions decreases, the probability of ignoring an alternative also decreases. We also find that the labelling format plays an important role in influencing visual fixation and the probability of considering a choice alternative. Most importantly, we find that these effects are more prominent for unhealthy products compared to healthy products. The results have important implications for the food industry and the policy-makers regarding the front-of-pack labels. The findings show that labels using traffic light colour coding are more likely to help consumers process information than other formats, such as no-colour coded numeric labels. This gives insights into other areas where communication is delivered via labels to encourage people to make informed choices.

JEL Classification: D12, D90, D91

Keywords
Front-of-pack labelling — food choice — decision-making — eye-tracking — latent variable model

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Introduction

Unhealthy eating has been identified as a significant factor in the increasing incidence of obesity, both in the UK and many other developed countries (Apovian, 2010), as well as in the increasing number of health conditions like heart disease and cancer (Lim et al., 2013). Therefore, understanding individuals' food choices plays an important role in mitigating nutrition-related issues. Accordingly, governments establish policy options and tools to tackle these issues to improve public health. One such policy surrounds the use of nutritional information on food packaging. This includes detailed nutritional descriptions of several components, such as fat, carbohydrates, protein, vitamins, fibre, and salt, provided on the back of food packaging. However, the format and level of detail can often be complex for the public to understand (Tarabella and Voinea, 2013). This has led to the development of simpler and more easily used versions of nutritional labelling placed on the front of the packaging.

Front of pack (FoP) nutrition labelling is a scheme that includes information on the energy value and nutritional content of food products sold. By making such information more prominently available at the time of purchase, FoP labelling can reduce the information asymmetry between consumers and food manufacturers (Verbeke, 2005). Their use has attracted much attention in the literature in many countries, including many European countries and the USA. In fact, in Europe, since the beginning of 2016, FoP nutrition labelling has been made mandatory under European Regulation 1169/2011. Over 80% of the food products sold in the UK have some form of FoP nutrition labelling (UK Department of Health, 2012). Although FoP nutrition labelling helps consumers make more informed choices by comparing various food products for their nutritional and calorie information, there are inconsistencies between the different nutrition labelling formats used. For example, some retailers and manufacturers use labels showing Guideline Daily Amounts (GDA), which indicates the amount of particular nutrients and calories for an average adult's healthy diet. In contrast, others use traffic light colour coding to highlight the level of fat, saturates (saturated fat), sugars and salt. Some retailers even use a mixture of the two formats. However, there is relatively little evidence on whether different FoP labelling formats influence consumers' choices and the visual attention people pay to these labels when making decisions. Alongside this, there is mixed evidence on the strength and weaknesses of these different formats (Borgmeier and Westenhoefer, 2009; Grunert et al., 2010). In particular, whether certain labelling formats lead to different decision-making processes when making food choices is relatively limited. This research sheds light on these issues.

This paper investigates the effect of different FoP nutritional labelling on individuals' decision-making processes and food choices. To do this, we merge a discrete choice experiment, a preference elicitation technique, with an eye-tracking experiment to explore the tendency to adopt heuristical decision processes. Overall, we find that our integrated method provides rich insights into explaining food choices and decision-making. Specifically, we find that the time someone spends looking at a choice alternative influences the probability of considering it. Thus it helps explain the labelling format more likely to help consumers process information. This gives insights into other areas where communication is delivered via labels to encourage people to make informed choices.

The structure of the paper is as follows; Study design section provides background information on the front of pack labelling; Data section introduces the discrete choice survey and the eye-tracking experiment; Modelling approach section introduces the data; Results and Scenario analysis sections outlines the model and provides the results before concluding the paper in Conclusions and future research section.

Study design

We investigate the effects of front-of-pack labelling on consumers' food choices and decision-making using an integrated method that brings together a discrete choice experiment (DCE) with an eye-tracking experiment.

Discrete choice experiment (DCE)

The discrete choice experiment is a stated preference elicitation technique in which participants are typically presented with hypothetical scenarios of products/services/goods, described according to a series of defined characteristics at various "levels", and asked to make a series of choices between different scenarios options. Our study presented participants with packets of crisps defined by their contents of four nutrients (salt, sugar, saturated fats, fats), calorie contents, and their prices. The complete list of attributes and their levels are presented in Table 1. We retrieved these levels by looking at typical nutrient values and the price of potato crisps in the market.

In order to create the FoP labelling, we used the guidelines created by the UK's Food Standards Agency. These guidelines set out a "best practice" procedure for how information should be displayed and the ideal formatting, including the colours to be used. The FoP system uses both traffic light system and Guideline Daily Amounts (GDA), indicating nutrient and calorie amounts (e.g. grams of fat or kilocalories for energy) and the percentage of "recommended daily intake" levels. The figures were all displayed as "per portion (30g)", and the colours were based on 100g of the product, as per the guidelines (UK Department of Health, 2012).

In order to investigate format variation, we generated four FoP label formats: (1) colour coding with numbers (e.g. grams of fat), (2) colour coding with text descriptors (e.g., low, medium, and high), (3) no colours but numbers, and (4) no colours but text descriptors. Figure presents examples of crisps packets having different FoP nutritional labels that we used in DCE tasks.

Attribute	Levels
Fat	3.6, 4.8, 6, 9 grams
Saturated fat	0.3, 0.5, 0.6, 1.2, 1.5, 2.1 grams
Sugar	0.6, 1.2, 1.8, 2.7 grams
Salt	0.3, 0.5, 0.6, 0.9 grams
Price	0.50, 0.60, 0.70, 0.80
Format	Colour-number
	Colour-text
	No colour-number
	No colour-text

Table 1. DCE attributes and their levels

To investigate format variation, we generated four FoP label formats: (1) colour coding with numbers (e.g. grams of fat), (2) colour coding with text descriptors (e.g., low, medium, and high), (3) no colours but numbers, and (4) no colours but text descriptors. Figure 1 presents examples of crisp packets with different FoP nutritional labels that we used in DCE tasks.

Figure 1. Examples of packets of crisps used in the study

The DCE survey was undertaken in a PC lab, where participants were presented with two packets of potato crisps options on a computer monitor, as seen in Figure 2. Before the experiment started, participants were provided with information on the experiment and instructed to choose one of the potato crisps presented to them that they preferred the most by pressing on the right/left arrow keys from the keyboard located in front of the monitor. The options presented to them varied in terms of nutritional attributes and the price, and the format of labels. Each participant was provided with 36 sequential choice tasks.

Figure 2. Examples DCE task

The way the scenario alternatives are described is based on an experimental design, ensuring:

- one- and two-way frequency balance of the attribute levels;
- balanced overlap between attribute levels across choice tasks; and
- near-orthogonality where levels are chosen independently of other levels so that each attribute level's effect (utility) may be measured independently of all other effects.

We generated the experimental design using Sawtooth Software with prohibitions on some combinations of fat and saturated fat content. These prohibitions were also based on the features of available crisps in the market. For example, when a product has 3.6 grams of fat, it cannot have 1.5 or 2.1 grams of saturated fat. Therefore, such inappropriate combinations were excluded when creating the experimental design. After designing the DCE survey, we piloted it with a small sample of individuals to check whether there were any ambiguities in wording and whether the length of the survey was manageable for respondents.

Eye-tracking experiment

An eye tracker was used during the choice experiment to record where and how long individuals fixated on the choice tasks. Again, the aim of collecting eye-tracking data was to explore participants' decision-making strategy – in this case, whether label formats influence time spent on decision-making.

In the experiment, we placed the SMI RED eye-tracker directly under the PC monitor (see Figure 3). Brand-specific software used for design and data handling included BeGaze 3.5, Experimental Centre 3.5, and iView X. A 5-point calibration procedure was used, and the sampling rate was 60Hz. This was a non-intrusive set-up with no need for glasses or a chin rest, allowing participants to feel more comfortable. The eye-tracker uses infra-red light transmitted by the device and subsequently reflects off the participant's pupils. It then receives (reflects) the light to determine the gaze position about the display screen and records the dwell time – how long individuals fixated on an area of interest, such as price, four nutrients and calorie information on the label. Visual stimuli, in other words, images of two crisp packages presented on screen were randomly presented to participants, who then indicated their preferred option by clicking on the right or left button on their computer mouse.

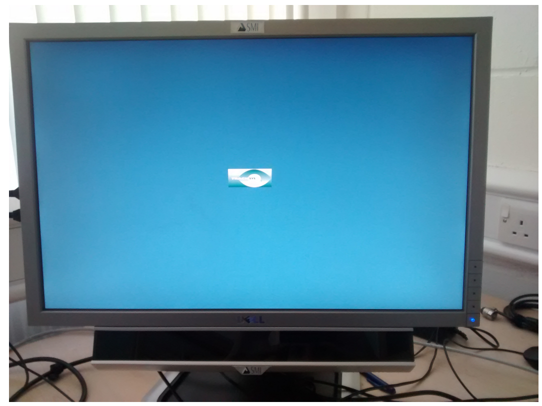


Figure 3. Eye-tracker

Data

We recruited 117 students at the University of Stirling in the UK to participate in the study. Each respondent answered DCE tasks while an eye-tracking device was used and a follow-up questionnaire after the experiment. Of these 117 participants, we used observations from 92 participants due to issues related to the quality of the eye-tracking data and missing responses to choice tasks. Each participant answered 36 choice tasks, resulting in 3,312 observations to use in our behavioural choice model.

Looking at the participants' characteristics, we find that the average age of the participants was 21 years old (SD=5.63), 34% of the participants were male, the majority ate 1-2 packets of potato crisps per week, and 78% were familiar with nutritional labels. The data from the follow-up questionnaire revealed that none of the participants had used eye-tracking equipment themselves or had any substantial knowledge or experience in the field of nutrition.

Modelling approach

We integrated the choice and eye-tracking data using a behavioural choice model, which we visually present in Figure 4. In this illustration, observed components are shown in rectangles, and unobserved components are shown in ellipses.

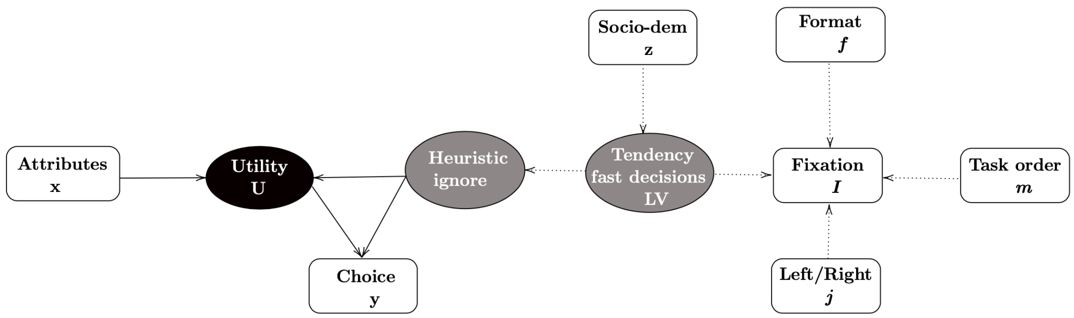


Figure 4. Behavioural choice model

Our modelling approach expands the typical choice model by considering the time spent on decision-making processes. In the typical choice model, the utility individual n obtains from choosing an alternative i is described by its attributes x. The individual then chooses the alternative, which gives them the highest utility under the assumption of full consideration of choice alternatives. The typical assumption of the random utility maximisation model is that individuals exhibit compensatory behaviour – i.e., consider all attributes and alternatives and make choices accordingly. However, it is plausible to assume that some individuals might not present a full compensatory choice behaviour. However, participants might adopt decision heuristics (short-cuts) when making choices, such as eliminating alternatives based on some decision criteria (Tversky, 1972) or ignoring some attributes (Campbell et al., 2016). Thus, the choice model needs to take into account "non-compensatory" behaviour to retrieve reliable estimates.

Our modelling specification expands this choice model by introducing a deterministic penalisation function, ϕ_{nis}, motivated by the constrained multinomial logit (CMNL) model, proposed by Martínez et al. (2009) in a route choice study. The idea of CMNL is to penalise the random utility maximisation (RUM) model for cases where a variety of constraints apply, for example, income, time, and choice attributes that violate individuals' limits (for more details, see Martínez et al. (2009)). In our study, our constraint is that individuals spent zero time looking at the front of pack labels. This includes the total time looking at all areas of FoP labels (e.g., calorie, price, nutrient contents). In this case, assuming that all individuals looked at the labels, and thus had non-zero time looking at labels, would result in erroneous model specification and estimates. Therefore, we adopt a two-stage approach, as motivated by Manski (1977) and adopted by Martínez et al. (2009). In the first stage, the model identifies the subset of individuals who spent non-zero time looking at the front-of-pack label. In the second stage, we apply the RUM framework complying with compensatory behaviour. As a result, under the CMNL specification, we specify our utility function as follows:

$$U_{nis} = \beta x_{nis} + \frac{1}{\mu}\ln(\phi_{nis}) + \varepsilon_{nis}, \tag{1}$$

where U_{nis} is the utility individual n obtains from choosing alternative i among J alternatives in choice occasion s; β_k are the marginal utility parameters to be estimated for each attribute defined by x; ϕ_{nis} is the probability that individual n considering alternative i within their choice set in task s, and it takes values between 0 and 1; μ is the scale parameter of the error term, ε_{ni}, which follows a Gumbel distribution, (0, μ). Note that the penalty increases by the inverse of the Gumbel scale parameter ($1/\mu$). In other words, when the scale parameter (μ) gets smaller, the utility dispersion gets higher, and as a result, the penalty on the RUM model increases. However, for identification purposes, μ is set to one.

The probability of considering an alternative, ϕ_{nis}, can be defined as a binomial logit. Note that our model differs from the model proposed by Martínez et al. (2009) because we do not introduce both lower and upper cut-offs for time spent on looking at labels, but just the lower cut-off point – i.e., zero. In light of this, we write ϕ_{nis} as follows:

$$\phi_{nis} = \frac{1}{1+\exp[\omega_{nis}]} \tag{2}$$

This probability of consideration, ϕ_{nis}, can be explained by various factors, such as right/left positioning of an alternative, order of the task (e.g., earlier vs later tasks), format of the label (e.g., colours vs numbers), and dwell time. We formally express the ω_{nis} as: $\omega_{nis} = \exp(\alpha + \beta_1 j + \beta_2 m + \beta_3 f + \beta_4 \mathscr{L})$. Here, j refers to the positioning of a choice alternative (left / right); m refers to task order; f refers to the format of the front of pack labels; and $\mathscr{L}_n$ is the latent variable for a tendency to make fast decisions. We define the latent variable as a function of socio-demographic characteristics:

$$\mathscr{L} = h(Z_n, \alpha) + \varepsilon_n, \qquad \varepsilon_n \sim N(0, \sigma_n^2) \tag{3}$$

To accommodate dwell time in the model, we use another logit expression to explain the tendency to have zero dwell time for an alternative. This expression includes the same explanatory variables as above,including the latent variable (LV):

$$\pi_{\text{fast}} = \frac{\exp(\psi)}{1+\exp(\psi)} \tag{4}$$

where $\psi = \alpha + \beta_5 j + \beta_6 m + \beta_7 f + \beta_8 \mathscr{L}$.

The overall behavioural choice probability under CMNL can thus be expressed as:

$$\Pr = \underbrace{\left(\prod_{s=1}^{S_n} \frac{\exp\left(\beta x_{nis} + \ln\left(\phi_{nis}\right)\right)}{\sum_{j=1}^{J} \exp\left(\beta x_{nis} + \ln\left(\phi_{nis}\right)\right)} \right)}_{\text{probability of a sequence of choices}} \underbrace{\left(\pi_{\text{fast}} \mathscr{I}_0 + (1-\pi_{\text{fast}}).(1-\mathscr{I}_0)\right)}_{\text{indicator probability}} \tag{5}$$

where $\mathscr{I}_0$ is a dummy (indicator) variable identifying whether an individual spent zero-time looking at a choice alternative (i.e., when dwell time is zero seconds from our eye-tracking data). All parameters are simultaneously estimated using maximum simulated likelihood. The estimation involves maximising the joint likelihood of the observed sequence of choices and dwell time, both conditional on the latent variable.

Results

Estimation Results

We report the estimation results in Table 2. Looking at the results, we observe that, on average, the price of crisps was the most disliked feature of the product, followed by salt and saturated fat. On the other hand, the sugar content was found to be relatively less important. Regarding the front-of-pack label format, we find that respondents prefer traffic-light colouring and numbers over the texts and no-colours. In fact, labels with texts are not preferred regardless of the use of traffic light colour coding.

Focusing on the penalty component of the model, ϕ, which we interpret as the probability of consideration, we see that the likelihood of this heuristical decision process increases when labels use colours and numbers instead of no-colours and texts. We also find that left alternatives are more likely to be within the consideration set than alternatives positioned on the right. The insignificant "tasks" parameter indicates that the consideration sets do not differ between the first and second half of the choice sequence. Moving our attention to the strongly significant latent variable (LV), we see that, as the LV increases, the probability of consideration reduces (i.e., the penalty increases). The LV has a positive impact on ψ, indicating that as the tendency to make fast decisions increases, the likelihood of not looking at the alternative increases. These are important findings, as it implies that the latent variable (of having fast decisions) jointly explains the propensity to consider and look at the alternative.

Moving to the other ψ interactions, we observe that alternatives presented on the left, having colour-coding and numbers, are more likely to have a non-zero dwell time. Left-right position bias is not unexpected as the direction indicated the way participants read the information (Campbell and Erdem, 2015; Foulsham et al., 2013). We see no gender variation in explaining the LV, tendency to exhibit a fast decision process.

	Estimate	Std. Error
β_{price}	-2.98	0.379***
β_{fat}	-0.198	0.024***
β_{satfat}	-0.362	0.057***
β_{sugar}	-0.121	0.034***
β_{salt}	-0.551	0.119***
ϕ: constant	-18.127	1.062***
ϕ: alt (left)	-0.411	0.244*
ϕ: tasks 1-18	-0.598	0.475
ϕ: Format: colour-number	13.506	1.303***
ϕ: Format: nocolour-number	-3.692	0.874***
ϕ: Format: colour-text	13.385	1.166***
ϕ: LV interaction	1.584	0.309***
ψ: constant	-0.661	0.352*
ψ: LV interaction	0.975	0.495**
ψ: alt (left)	-0.572	0.14***
ψ: tasks 1-18	-0.07	0.075
ψ: Format: colour-number	-0.308	0.146**
ψ: Format: nocolour-number	0.016	0.086
ψ: Format: colour-text	-0.311	0.138**
LV: male	-0.011	0.559
LV: sigma	2.574	1.301**
LL		-4530.638
N		3312

***,**,* indicate significance at the 1% , 5%, and 10% levels, respectively.

Table 2. Estimation results

In summary, the choice model's significant latent variable interaction indicates that heuristical decision-making processes explain the probability of considering an alternative. We find that traffic light colour coding labels are more likely to help consumers process information than other formats, such as no-colour coded numeric labels. Underlying reasons for fast (or slow) thinking can be better explained by unobserved factors (e.g., health concerns of individuals, health conditions, and other individual characteristics), as evident from the significant LV standard deviation.

These findings are in line with some previous research. For instance, a study report involving comparisons of various food products found that while TLS (equivalent to coloured labels with text descriptors), GDA (equivalent to non-coloured labels with numbers), and combined TLS/GDA (equivalent to coloured labels with numbers) systems all produced high accuracy for "healthiness" judgements, the combined TLS/GDA system produced significantly higher accuracy than the other systems (Synovate, 2005). Malam et al. (2009) found that ease of understanding was strongest when the FoP labels included GDA information, colours, and text descriptors, compared to other systems. Hodgkins et al. (2012) compared several different formatting variations of FoP label, with a particular focus on "directiveness" compared with "non-directiveness". Aspects such as colour coding that are easy to process quickly were categorised as "directive", while numerical nutritional details that require more deliberation were categorised as "non-directive". They found that individual differences, task demands, and food type can all influence the relative effectiveness of these differing label aspects. They also suggested that, in general, "directive" characteristics lead to greater ease of understanding and more consistent influence and "non-directive" details can enhance trust for the consumer. Even if not using the extra details, consumers may feel that the source of information can be more trusted due to this extra detail. They propose that an ideal FoP label would include both "directive" details (e.g., colours) in order to aid ease of use and be appropriate for certain members of the public, and "non-directive" details (even beyond that contained in GDA labels) which may suit more knowledgeable people and enhance trust, while satisfying the consumers' need to believe they are acting rationally.

There are some contradicting results in the literature as well. In particular, some studies suggest that the addition of colour coding is more effective when displayed in a simpler form than the combined TLS/GDA systems. Borgmeier and Westenhoefer (2009) found that the simpler TLS format (i.e. colours without numerical details) was the most effective in enhancing accuracy. Thorndike et al. (2014) found that healthier food choices were made when foods (in a cafeteria) were labelled with colours. Their system, however, was an even simpler format than TLS with only "healthy" or "unhealthy" foods labelled in green or red, respectively. Grunert et al. (2010) found no clear difference between these three formats but did find all were considered easy to understand.

Clearly, there are different findings among the research, but the EU/UK standard practice guidelines encourage using a TLS/GDA combination system, with both colours and numerical details included (UK Department of Health, 2012). These guidelines aim to promote consistency in labelling. Additionally, they also describe a system that is believed to be more effective for a larger proportion of the population than other systems. The findings of this research provide support for the use of this system.

Scenario analysis

In order to understand the implications of our findings, we present a scenario analysis where we simulate the probability of looking at the healthy option and the choice probability of the health option using the model estimates for different values of the latent variable.

We define the healthy option where all nutrients (fat, saturated fat, sugar and salt) take the lowest value, whereas the unhealthy option takes the highest amount of nutrients. We also vary the position of the healthy and unhealthy product and their formats when presenting the choice tasks. When we use colours and numbers for the unhealthy option, we observe that the probability of looking at the healthy option decreases when the latent variable increases (i.e., values on the x-axis), regardless of how the healthy product is presented (e.g., colour or no-colour). This signals the tendency to exhibit a fast decision process (Figure 5 (a)). This also holds no matter where the healthy option is on the presented pair-comparison – i.e., left or right, as evident from the top and bottom set of graphs, respectively.

When the unhealthy option is presented without any colours and with text descriptors, we observe a similar pattern - i.e., when LV increases, the probability of looking at the healthy option decreases (Figure 5 (b)). This suggests that our latent variable is a good measure of someone's tendency to exhibit a fast decision process and is independent of how the choice alternatives are presented (i.e., format, position, sequence).

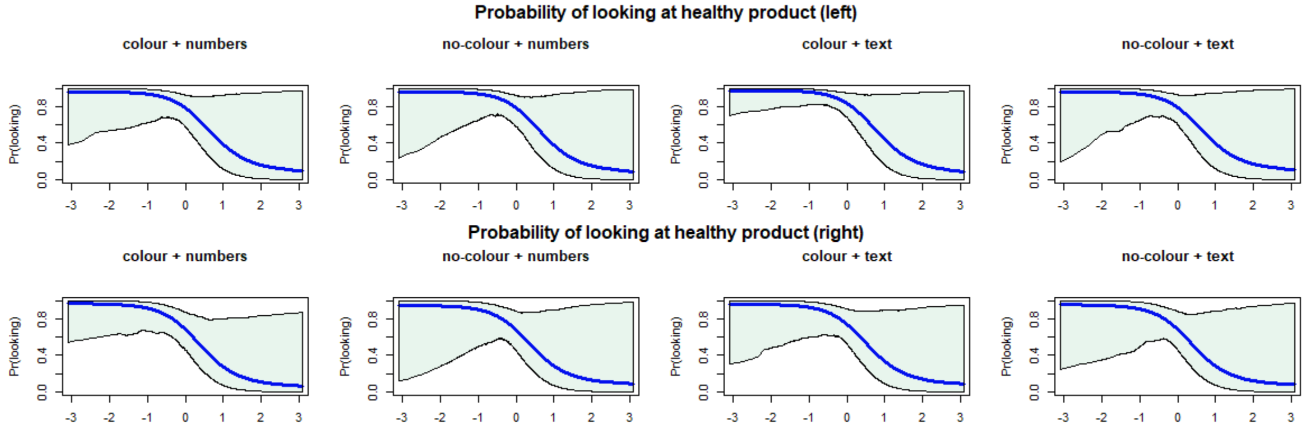
Similarly, we vary the format, position, and sequence of the choice tasks and calculate healthy options' choice probabilities (Figure 6). As seen from Figure 6 (a), when the unhealthy option is presented with colour-coded labels with numbers, the probability of healthy choice increases when the latent variable increases, indicating when the tendency to have fast decisions increases, individuals are more likely to choose the healthy option if the unhealthy option is visually salient through the colour-coding. When the unhealthy option does not have colour-coding, the probability of a healthy choice does not increase no matter how it is presented (Figure 6 (b)). This indicates the importance of how the unhealthy option is presented rather than the healthy option is presented.

Conclusions and future research

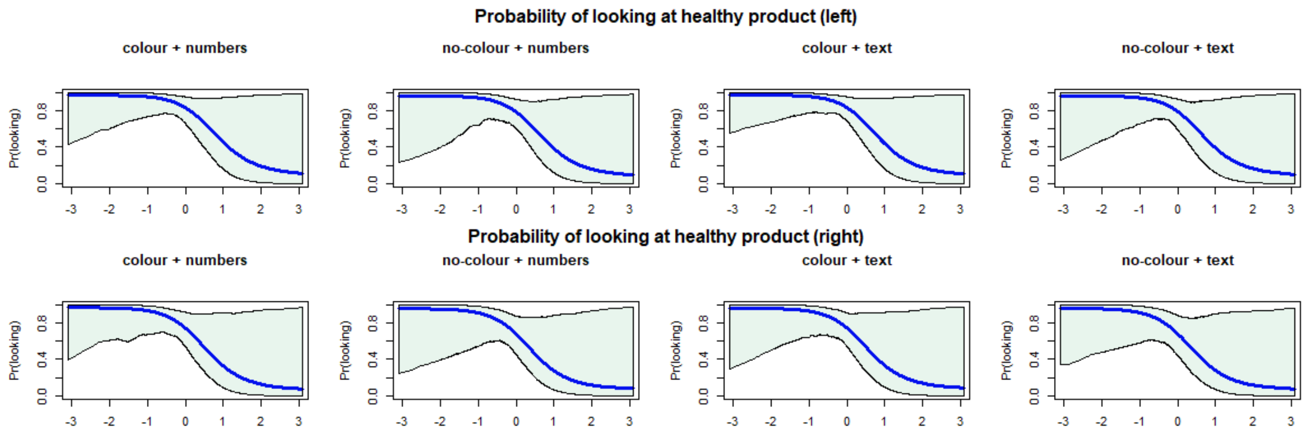
The front-of-pack labelling provides nutritional information to consumers intending to motivate better and healthier food choices. In order to deliver this, labels are presented using formats, such as colour codes and numeric or text descriptors for the levels of nutrients included on the label. Such variations in label formats are found to result in different levels of effectiveness and influence in the literature (Borgmeier and Westenhoefer, 2009; Tarabella and Voinea, 2013).

This research presents a discrete choice and an eye-tracking experiment investigating individuals' preferences and decision-making when different FoP nutrition labelling is used. Particularly, we explore whether the format of front-of-pack labels leads to heuristical decision processes. To explore this, we use an integrated behavioural choice model, where visual attention is coupled with decision-making heuristics in the form of a CMNL model.

Overall, we find that our integrated method provides rich insights into explaining food choices and decision-making.



(a) Unhealthy option is presented with colours and numbers at the left and right of the pair comparison



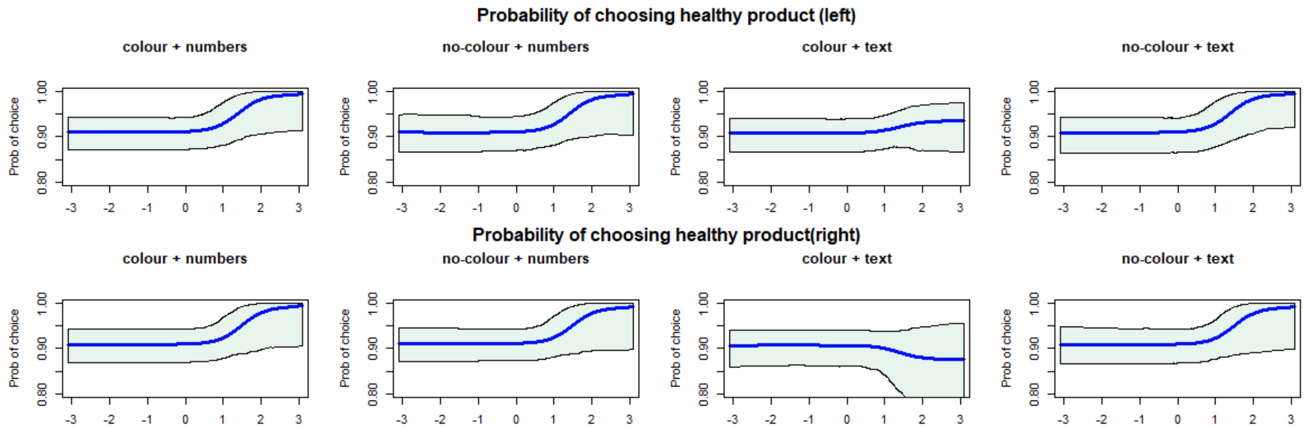
(b) Unhealthy option is presented with no-colours and text descriptors at the left and right of the pair comparison

Figure 5. Probability of looking at healthy options

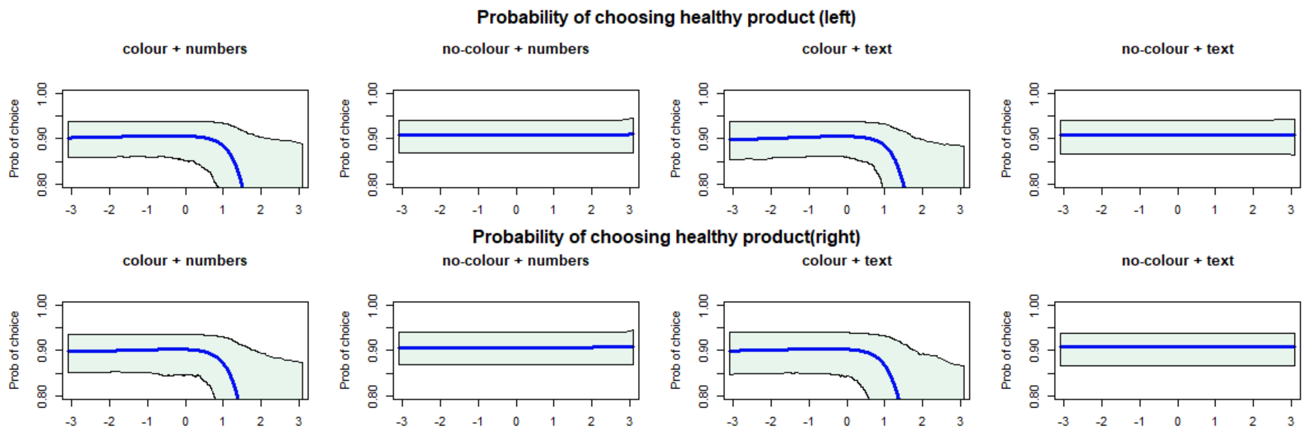
For example, significant latent variable interaction in the choice model indicates that the fast/slow decision process explains the probability of considering an alternative. Specifically, the likelihood of ignoring an alternative decreases when colour-coded labels are used. This suggests that labels with colour coding are more likely to help consumers process information as compared to other formats, such as no-colour coded numeric labels. This mainly has important implications for the food industry and the policy-makers regarding FoP labels. For instance, consumers' understanding and evaluation of nutrients (e.g., salt and fat content) of food products can influence their purchasing behaviour (Schor et al., 2010). Therefore, it is important to communicate the nutritional information to consumers so that they can easily process it. This also gives insights into other areas where communication is delivered via labels to encourage people to make informed choices.

Our results also suggest further research in the field. In this paper, we focus on non-attendance as decision heuristics. Although there is much research on explaining attribute non-attendance using eye-tracking data (Balcombe et al., 2010; Spinks and Mortimer, 2015; Van Loo et al., 2015) assuming that not fixating on areas of interest are taken as non-attendance, there is a possibility that attendance was still possible via peripheral vision. This is especially feasible as the label sections (i.e. each nutrient) are relatively small and placed together. This effect via peripheral vision is less reasonable for the "no colours" conditions. Therefore, future research should consider differential results for the presence or absence of colour. In other words, zero dwell time or fixation count does not guarantee the existence of attribute non-attendance. The extension of this research will investigate this issue further and develop behavioural choice models that accommodate them.

Further, the participants used in the current study were all university students and mainly between 18 to 26 years of age. Clearly, this limits the conclusions that can be generalised and does not provide relevant data for populations that regularly shop for food, such as parents (albeit some participants were parents). Even though this limits the conclusions' scope, it is worth noting that there is evidence suggesting adolescents make more health-conscious decisions when using the food TLS compared with other systems and can be more influenced



(a) Unhealthy option is presented with colours and number at the left and right of the pair comparison



(b) Unhealthy option is presented with no-colours and text descriptors at the left and right of the pair comparison

Figure 6. Choice probability of healthy options

by the TLS than other systems (Babio et al., 2014). Additionally, since food health and obesity are ongoing problems, it is necessary to collect data related to future generations to aid in creating more effective tools that will maintain their effectiveness.

Notwithstanding these potential limitations, our findings provide compelling evidence for further research in this area. Using an integrated method that utilises DCE and an eye-tracking experiment provides richer insights into explaining food choices and decision-making processes.

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References

Apovian, C.M., 2010. The causes, prevalence, and treatment of obesity revisited in 2009: what have we learned so far? The American Journal of Clinical Nutrition 91, 277–279. 10.3945/ajcn.2009.28473A.

Babio, N., Vicent, P., Lopez, L., Benito, A., Basulto, J., Salas-Salvado, J., 2014. Adolescents' ability to select healthy food using two different front-of-pack food labels: a cross-over study. Public Health Nutrition 17, 6. 10.1017/S1368980013001274.

Balcombe, K., Fraser, I., Falco, S.D., 2010. Traffic lights and food choice: A choice experiment examining the relationship between nutritional food labels and price. Food Policy 35, 3. 10.1016/j.foodpol.2009.12.005.

Borgmeier, I., Westenhoefer, J., 2009. Impact of different food label formats on healthiness evaluation and food choice of consumers: a randomized-controlled study. BMC Public Health 9, 184. 10.1186/1471-2458-9-184.

Campbell, D., Erdem, S., 2015. Position bias in best-worst scaling surveys: A case study on trust in institutions. American Journal of Agricultural Economics 97, 526. 10.1093/ajae/aau112.

Campbell, D., Morkbak, M.R., Olsen, S.B., 2016. Response time in online stated choice experiments: the non-triviality of identifying fast and slow respondents. Journal of Environmental Economics and Policy 1. 10.1080/21606544.2016.1167632.

Foulsham, T., Gray, A., Nasiopoulos, E., Kingstone, A., 2013. Leftward biases in picture scanning and line bisection: A gaze-contingent window study. Vision Research 78, 14–25. 10.1016/j.visres.2012.12.001.

Grunert, K.G., Wills, J.M., Fernandez-Celeman, L., 2010. Nutrition knowledge, and use and understanding of nutrition information on food labels among consumers in the uk. Appetite 55, 177–189.

Hodgkins, C., Barnett, J., Wasowicz-Kirylo, G., Stysko-Kunkowska, M., Gulcan, Y., Kustepeli, Y., 2012. Understanding how consumers categorise nutritional labels: A consumer derived typology for front-of-pack nutrition labelling. Appetite 59, 806–817. 10.1016/j.appet.2012.08.014.

Lim, S.S., Vos, T., Flaxman, A.D., et al., 2013. A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990-2010: a systematic analysis for the global burden of disease study 2010. The Lancet 380, 2224–2260. 10.1016/S0140-6736(12)61766-8.

Malam, S., Clegg, S., Kirwan, S., McGinigal, S., 2009. Comprehension and use of uk nutrition signpost labelling schemes. Food Standards Agency (Report). 24. food.gov.uk/multimedia/pdfs/pmpreport.pdf.

Manski, C.F., 1977. The structure of random utility models. Theory and decision 8, 229.

Martínez, F., Aguila, F., Hurtubia, R., 2009. The constrained multinomial logit: A semi-compensatory choice model. Transportation Research Part B: Methodological 43, 365–377.

Schor, D., Maniscalco, S., Tuttle, M.M., Alligood, S., Reinhardt Kapsak, W., 2010. Nutrition facts you can't miss: The evolution of front-of-pack labeling: Providing consumers with tools to help select foods and beverages to encourage more healthful diets. Nutrition Today 45, 22–32. 10.1097/NT.1090b1013e3181cb4561.

Spinks, J., Mortimer, D., 2015. Lost in the crowd? using eye-tracking to investigate the effect of complexity on attribute non-attendance in discrete choice experiments. BMC Medical Informatics and Decision Making 16, 14. 10.1186/s12911-016-0251-1.

Synovate, 2005. Quantitative evaluation of alternative food signposting concepts: report of findings,Nov 2005, [COI Job number: 265087]. Technical Report. Food Standards Agency. COI Job number: 265087.

Tarabella, A., Voinea, L., 2013. Advantages and limitations of the front-of-package (fop) labeling systems in guiding the consumers' healthy food choice. Amfiteatru Economic 15, 198–209.

Thorndike, A.N., Riis, J., Sonnenberg, L.M., Levy, D.E., 2014. Traffic-light labels and choice architecture: Promoting healthy food choices. American Journal of Preventive Medicine 46, 143–149. 10.1016/j.amepre.2013.10.002.

Tversky, A., 1972. Elimination by aspects: A theory of choice. Psychological review 79, 281.

UK Department of Health, 2012. Food labelling consultation. Technical Report. Food Standards Agency. Accessed: March 2015.

Van Loo, E.J., Caputo, V., Nayga, R.M., Seo, H.S., Zhang, B., Verbeke, W., 2015. Sustainability labels on coffee: Consumer preferences, willingness-to-pay and visual attention to attributes. Ecological Economics 118, 215–225. 10.1016/j.ecolecon.2015.07.011.

Verbeke, W., 2005. Agriculture and the food industry in the information age. European Review of Agricultural Economics 32, 347–368.