The eyes have it: using eye tracking to inform information processing strategies in multi-attributes choices

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ABSTRACT

Whilst choice experiments (CEs) are widely applied in economics to study choice behaviour, understanding of how individuals' process attribute information remains limited. We show how eye-tracking methods can provide insight into how decisions are made. Participants completed a CE while their eye movements were recorded. Results show that while the information presented guided participants' decisions, there were also several processing biases at work. Evidence was found of (i) top-to-bottom, (ii) left-to-right and (iii) first-to-last order biases. Experimental factors - whether attributes are defined as 'best' or 'worst', choice task complexity and attribute ordering - also influence information processing. How individuals visually process attribute information was shown to be related to their choices. Implications for the design and analysis of CEs and future research are discussed.

1. INTRODUCTION

Recent years have seen an increase in the use of Choice Experiments (CEs) to value non-marketed commodities (Clark et al, 2014; de Bekker-Grob et al, 2012). Modelling CE responses typically rests on the assumption of utility maximisation (Manski, 1977). However, it is well documented in the decision making literature that humans deviate from such choice behaviour. Decision-making has been shown to be affected by factors such as number of alternatives, number of attributes, time pressure, and similarity between alternatives, as well as the decision environment and person characteristics (DeShazo & Fermo, 2002; Day et al, 2012; Day & Pinto Prades, 2010; Gigerenzer & Todd, 2001). For example, studies asking participants to verbally express their reasoning processes while making decisions demonstrate that individuals behave as "cognitive misers", adapting effort invested in making a decision to context and resources (Shugan, 1980; Payne et al, 1993).

Methods to investigate how participants make multi-attribute choices in applied economics are limited. Early research tested for lexicographic preferences (e.g., do respondents always choose the cheapest option?) (Saelensminde, 2006; Rosenberger et al, 2003; McIntosh & Ryan, 2002). However, lexicographic preference structures may be consistent with trading, indicating strong preferences rather than violation of the continuity axiom. Research then tried a range of other approaches. For example, Ryan et al (2009) attempted to probe into underlying decision processes by using "think aloud" methods where participants are asked to vocalize their ongoing decision processes. Whilst finding evidence that 'irrational' responses can be rationalised, respondents struggled to think aloud. Another strategy involves determining what makes people ignore information (attribute non-attendance, ANA), either by asking participants to state which attributes they consider when making their choices (Scarpa et al, 2013; Hole et al, 2013), or by inferring ANA from their choices (Hole 2011; Campbell et al, 2011; McNair et al, 2012). However, these two approaches suffer from limitations. While the stated ANA approach is limited by participants' ability to recall how they reached their decisions (or to critically reflect on how they make their decisions), inferred ANA relies on questionable statistical considerations and provides no understanding of why an attribute is ignored (Hess et al, 2013; Hensher et al, 2013).

Recently, it has been suggested that eye-tracking may provide a powerful tool for better understanding economic behaviour (Lahey & Oxley, 2016). A limited but growing number of studies have explored the role of visual attention in economic decision making (Caplin & Dean, 2008; Knoepfle et al, 2009; Wang et al, 2010; Reutskaja et al, 2011). In the CE literature, a small number of studies have used eye-tracking to improve the modelling of responses, with a focus on attribute non-attendance (Balcombe et al, 2015; Krucien et al, 2017; Van Loo et al, 2015; Uggeldahl et al, 2016; Meiβner et al, 2016; Spinks & Mortimer, 2015). Our novel work extends this literature, exploring how eye-tracking can be used to better understand how respondents interact with the choice tasks and process multi-attribute information in CEs.

Section 2 describes the design of the experiment, while Sections 3 and 4 describe how we link eye movements to choice processes, using fixation times (the total time spent on a piece of information) (Section 3) and fixation transitions (how often the eye shifts from one piece of information to another) (Section 4). Section 5 investigates the link between eye movements and choice behaviour. Across all analyses, we consistently find that information processing is subject to biases (in the order in which information is processed) and experimental factors (whether attributes defined as best or worse, difficultly of task and order of attributes). We also demonstrate that choices can be better modelled when eye-tracking data is incorporated, meaning that eye movement information explains people's choices beyond what information is presented to the participants. The results have important implications for the design and analysis of CEs, which will be discussed. Section 6 discusses limitations of our study, identifying important areas for future research. Section 7 offers concluding comments.

2. DESIGN OF THE EXPERIMENT

2.1 Choice experiment

Participants' choices were recorded for an existing CE on preferences for health & lifestyle (H&L) programmes to reduce obesity (Ryan et al, 2015). Each programme was described by seven attributes (Table 1). Participants were presented with 14 choice tasks: two warm up (non-experiment) tasks (#1 and #2), and 10 experimental tasks intermixed with a monotonicity and stability check. The warm-up tasks, used to familiarise participants with the format of the choice tasks, were dropped for the eye-tracking analyses. Participants were asked to select their preferred option among two generic H&L programmes (i.e., Programme A vs. B) and an opt-out ("Current situation") option (Figure 1). The order of the tasks was randomised across participants. Choice tasks were presented on a computer screen. No time limit was imposed.

2.2 Experimental manipulation

Participants were allocated to one of two experimental conditions. In the initial experiment (Experiment 1, N=28), attributes were presented (from top to bottom) in the following order: PROGRAMME, WEIGHT, GOAL, DIABETES, HBP, TIME, and COST. In the second experiment (Experiment 2, N=30), the order of the attributes was reversed (i.e., COST; TIME; …; WEIGHT; PROGRAMME) and the location of the choices was switched (Left ↔ Right). The experiments were otherwise identical.

2.3 Eye tracking

The CE was completed in a dedicated eye-tracking laboratory and eye movements were recorded using an eye tracker (EyeLink 1000, SR Research). The eye tracker was calibrated for each participant using the system's default nine-point procedure. To avoid large head movements we used a combined head-and-chin rest. The data were divided into *fixations* (i.e., periods where the eyes remain relatively still) and *saccades* (i.e., fast eyes' movements during which information processing is suppressed). In line with the eye movement literature, we assume that information extraction only took place during the fixations and that a minimum of 50 milliseconds (ms) was needed for *meaningful* extraction of information (Tatler et al, 2006). Fixations were analysed in terms of where they were directed to with respect to 24 regions of interest (ROI) (Figure 1).

The initial dataset included 37,784 fixations, recorded from 58 participants responding to 12 choices. After excluding fixations of less than 50 ms, 36,862 fixations remained: fixations on the column labels (4.6%); fixations on the multi-attribute content of the two options (84.7%); fixations on the descriptive column (7.6%); and fixations on blank space (3.1%). We further excluded fixations on column labels and blank space, resulting in 34,023 observations for analysis.

2.4 Participants

The 58 participants were students or former students from the University of Aberdeen (UK) recruited using online advertisement on a first-come-first-served basis. They took part in return for course credit or participated without reimbursement. The first 28 participants were allocated to Experiment 1 and the following 30 participants to Experiment 2. The study was approved by the local ethics committee.

The two samples did not differ in terms of socio-demographic characteristics. Males made up 52% of the sample (13/25) in Experiment 1 and 31% (9/29) in Experiment 2 ($\chi_2 = 1.653$; $P = 0.198$). Information about height and weights was used to compute the body mass index (BMI) - 72% (18/25) of participants had a *normal* BMI in Experiment 1 versus 69% in Experiment 2 (20/29) ($\chi_2 < 0.001$; $P > 0.999$). The two samples were also similar in terms of age, with a mean age of 20.83 (SD = 1.73) and 20.48 (SD = 2.33) for Experiments 1 and 2 respectively ($t = 0.614$; $P = 0.542$).

3. DETERMINANTS OF FIXATION TIMES

A range of measures have been developed to analyse visual attention (e.g., fixation time, fixation frequency/count, pupil dilation) (Duchowski, 2007; Holmqvist, 2011). We focus on the total fixation time (FT) on each ROI, previously used as a measure of information interest and difficulty (Rayner, 1998). To avoid strong effects of long fixations on a piece of evidence, and to reduce the skew of the distribution, we used the natural logarithm of FT, which was computed for each ROI (see Figure 1) at the participant by task level. Using mixed effects linear models, we investigate the extent to which ln(FT) is influenced by the following CE factors:

- The LEFT parameter (β_1) captures the systematic effect of a ROI belonging to the left alternative compared to the right. Such an effect would be consistent with a "left-to-right" reading bias where participants pay more attention to information presented on the left (Rayner 1978, 1998; Guo et al, 2009; Durgin et al, 2008). Leftward biases are also found in other tasks, including digit comparison (Loetscher et al, 2008), picture scanning and line bisection (Foulsham et al, 2010), visual search (Durgin et al, 2008), reading Chinese characters and face perception (Butler et al, 2005; Everdell et al, 2007; van Belle et al, 2010). We expect participants to spend more time looking at the left options (**H1: $\beta_1 > 0$**).

- Two POSITION parameters capture the effects of the attributes position within the choice tasks. (β_2) and (β_3) measure respectively the effect of being *top* located (1st or 2nd position) and *bottom* located (6th or 7th position) versus being *middle* located (i.e., 3rd, 4th, or 5th position). This would also be consistent with typical reading patterns, and has been found in other domains such as visual search (Durgin et al, 2008). Within the CE literature there is evidence of ordering effects on estimated preferences (Kjær et al, 2006; Scott & Vick, 1999). Thus, first and last consulted pieces of information may receive a visual attention *bonus-malus*. We expect fixation times to differ for the top (**H2[a]: $\beta_2 \neq 0$**) and bottom located attributes (**H2[b]: $\beta_3 \neq 0$**).

- The two LEVEL parameters (β_4, β_5) capture the effects of attributes' value, either BEST or WORST, on visual attention. An attribute is classified as BEST when it is set at its *most desirable* level (e.g., lowest price) and WORST when set at *least desirable* level (e.g., highest price) (Table 1). We expect extreme information, either BEST or WORST, to be more psychologically salient (compared to INTERMEDIATE), thus attracting more attention (**H3[a]: $\beta_4 > 0$; H3[b]: $\beta_5 > 0$**). In line with loss aversion, participants are expected to be more sensitive to negatively framed information (Kahneman et al, 1991). We therefore expect participants to be more attentive to WORST than BEST information (**H3[c]: $\beta_4 < \beta_5$**). Our classification of attributes' levels as BEST, INTERMEDIATE or WORST is based on results from Ryan et al (2015) which administered the same CE questionnaire to a representative sample of the UK population.

- Two TRIAL parameters (β_6, β_7) capture the effect of task sequence (i.e., position of the choice tasks within the questionnaire). Previous studies have reported effects of task ordering on the consistency of respondents' choices (Day et al, 2012; Mantonakis et al, 2009; Bateman et al, 2008), suggesting *learning* and *fatigue* effects. We assume that as respondents progress through the choice tasks, they become more efficient in their information search, reducing fixation times on the ROI (**H4[a]: $\boldsymbol{\beta_6 < 0}$**). However this effect is expected to become marginally smaller over the sequence of tasks (**H4[b]: $\boldsymbol{\beta_7 > 0}$**).

- The DIFFICULTY parameter (β_8) captures the impact of choice difficulty. Shugan (1980) argues that difficulty is inversely related to perceptual similarity - highly different options are more difficult. As alternatives become less similar, the variance in the values on the attributes across alternatives increases. This can be captured by the dispersion of the standard deviation (DSD) among attribute levels across alternatives (DeShazo & Fermo, 2002)[1]. A priori it is hypothesised that as DSD increases, choice sets become less similar, and participants spend more time processing the multi-attribute information (**H5: $\boldsymbol{\beta_8 > 0}$**).

- The EXPERIMENT parameter (β_9) captures the effect of reversing the order of attributes and two choice options (over and above LEFT and POSITION). Using brain imaging, Karmarkar et al (2015) found that different orderings of product features was associated with different decision rules/objectives i.e. when the product price was presented first, participants were more likely to focus on whether the product was worth its price. We expect fixation times to significantly differ across experiments (**H6: $\boldsymbol{\beta_9 \neq 0}$**).

We thus estimate:

$$\ln(\mathrm{FT_{ntr}}) = \beta_0 + \beta_1\mathrm{LEFT_{ntr}} + \beta_{2:3}\mathrm{POSITION_{ntr}} + \beta_{4:5}\mathrm{LEVEL_{ntr}} + \beta_{6:7}\mathrm{TRIAL_{ntr}} + \beta_8\mathrm{DIFFICULTY_{ntr}} + \beta_9\mathrm{EXPERIMENT_{ntr}} + \omega_\mathrm{n} + \varepsilon_\mathrm{ntr} \qquad (2)$$

Where ($\mathrm{FT_{ntr}}$) indicates the fixation time on ROI (r) by respondent (n) at task (t). The errors (ω, ε) are assumed to be multivariate normally distributed and uncorrelated. Given that we use ln(FT) as the dependent variable, estimates can be interpreted as the % change in the fixation time by taking their exponent (i.e., exp(β)).

Results are presented in Table 2. Attributes of the left option were fixated on average +16% longer than those of the right option, suggesting a *left-to-right bias* in visual attention, in agreement with studies in other domains (see above). Part of this bias may be the result of the reading direction (left-to-right) in

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[1] The entropy measure is often used to capture task difficulty in CEs, describing the similarity of alternatives. Entropy is typically constructed using participant responses, creating an endogeneity problem i.e. entropy is a function of the probability of selecting each of the available alternatives, and thus may be a consequence of fixation time (rather than vice versa). We thank the Reviewer for this comment and thus use the DSD measure (which does not rely on respondent preferences). Appendix 1 compares the results using Entropy and DSD measures, the main results remain unchanged.

our participants and an interesting future direction would therefore be to study whether this bias is reversed when using a language with right-to-left reading direction (e.g., Arabic, Farsi, Hebrew, and Urdu) This visual bias may explain why CEs often find a significant constant term in generic choices. This finding suggests randomising the order of the alternatives within the choice tasks may improve the quality of CE data.

The first two attributes were looked at longer than the middle positioned attributes (+ 30%) whilst the bottom located attributes were looked at less (- 16%). These effects indicate a top-to-bottom visual bias when processing vertically presented (multi-attribute) information. Our finding suggests that observed top-to-bottom biases in CE may have their origin in stronger visual attention to attributes shown at the top. This suggests it is important to randomise the order of attributes. We suggest that this randomization is best done at the participant level (i.e., the order of the attributes would differ across participants but remains the same for all tasks faced by the same participant), because otherwise, participants have to adopt to a new order of attributes on every single choice.

Negatively (WORST) framed attributes were less looked at (- 4%), while positively (BEST) framed attributes were associated with longer fixation times (+ 9%). The finding suggests respondents give relatively more consideration to attributes with positive outcomes, consistent with Dawes' rule (Dawes, 1979), where alternatives with the highest number of positive aspects are chosen more often. Note that this finding is inconsistent with loss aversion, which predicted that negatively framed attributes would be fixated for longer. A possible reason for failing to find evidence of loss aversion may be that we dealt with hypothetical (non-consequential) choices, and it would therefore be interesting to determine whether the same result is obtained for actual choices (e.g., people making decisions in a doctor's surgery). Alternatively, future studies could examine whether one of the approaches to mitigate such hypothetical bias (e.g., cheap talk script, oath protocol) (Carlsson et al, 2005; Jacquemet et al, 2013; Özdemir et al, 2009) influences the bias towards positively frames attributes that we found here.

Both TRIAL variables had a significant effect on fixation time. The significant and negative trial number effect indicates that as participants progress through the sequence of tasks they spend less time looking at the different ROIs (*first-to-last bias*). The quadratic effect indicates that the marginal change in fixation time decreases over time. This result suggests that first observed choices could be contaminated by participants adjusting to the task and respondents may change their choice behaviour(s) during the study. Such an interpretation would agree with findings showing significantly longer responses time for the 1st task (Borjesson & Fosgerau, 2015). The present results, because we used 2 warm-up trials, suggests that longer fixation times last beyond the first task. It is therefore important to randomise the order of choices across participants, so that in the average data, such effects can be minimized.

The DIFFICULTY (DSD) parameter describes a positive relationship between task difficulty and visual attention. Participants spend more time fixating attributes when facing difficult choice tasks. This result is important for the design of CEs. While on the one hand, one would like to maximize the information gained from each trial by making the choice tasks more challenging, it could, on the other hand, wear out participants. This is in line with suggestions that *statistical efficiency* (i.e., information gained from each choice) is negatively correlated with the *respondents' efficiency* (i.e., the ability of participants to make informed decisions) (Viney et al, 2005; Flynn et al, 2016). Our study suggests that although increased statistical efficiency could wear participants out, it seems to improve respondents' attention, possibly leading to more informed decisions. The question arises to when this positive benefit on attention breaks down (e.g., after how many trials), which could be an interesting topic for future research.

The EXPERIMENT variable significantly contributed to the prediction of the fixation times. This means that the ordering of the attributes influenced fixation times beyond the effects of the attributes being left or right, or top or bottom. This suggests that besides considering what attributes to include (e.g., Coast et al, 2012), the design of CEs should also consider in what order the attributes are presented, particularly when computerised CEs are employed. When randomising is not an option (e.g., for pen-and-paper surveys), a second best solution may be to define "experientially meaningful configurations" (Hensher & Truong, 1985), which uses an ordering of attributes that is consistent with different steps in the process involved (e.g., for a medical appointment, the delay to get an appointment, the distance to travel, the waiting time, the length of consultation and out-of-pocket expense).

4. DETERMINANTS OF FIXATION TRANSITIONS

So far, we have only considered how long people look at attributes. This, however, discounts temporal information on the order in which attributes are processed. There are indications that the order of processing is important for decision making. For example, Armel et al (2008) showed that first fixated product (option) was more likely to be selected *ceteris paribus*. Likewise, participants are more likely to choose the option they look at last (Shimojo et al, 2003). To analyse order effects, we here examine transitions (i.e., eye-movements between ROI) as a function of time in the trials (percentage of the trials). We define four transition categories: ***option-wise*** (vertical reading) where participants move their eyes across ROI belonging to the same option (e.g., TIME [A] → COST [A]); ***attribute-wise*** (horizontal reading) where participants compare options on an attribute-by-attribute basis (e.g., COST [A] → COST [B]); ***refixations*** where participants consecutively fixate on the same ROI (e.g., COST [A] → COST [A]) and ***hybrid*** where participants move their eyes across ROI belonging to different options (e.g., TIME [A] → COST [B]). If people first form an overall impression of each choice option and then compare these overall impressions, we expect more option-wise transitions. If they compare the attributes of the two choice options directly, we expect more attribute-wise transitions.

Our dataset initially included 34,023 transitions. Those corresponding to a transition from the descriptive column (i.e. ROI 1 to 8 in Figure 1) were excluded, leaving 29,641 (87.1 %) transitions: 13,548 (45.7 %) refixations; 8,645 (29.2 %) option-wise; 4,898 (16.5 %) attribute-wise; and 2,550 (8.6 %) hybrid. (Detailed information about transitions is provided in Supplementary Material) Figure 2 shows the time-course of transitions across choices, clustered into 10 time bins for each trial (i.e., beginning of the information processing period [0-10%]; …; end of information processing period [90-100%]). Visual information processing mainly consists of refixations and option-wise transitions: participants initially (i.e., first three time bins) process the multi-attribute information mainly with refixations before exploring the content of each option separately (i.e., option-wise transitions).

We investigate transitions as a function of three task-related variables: TRIAL (Task order); Dispersion of Standard deviation [DSD] (Task difficulty); and EXPERIMENT (Experiment 1 or 2). As the dependent measure, we use the Search Measure (SM) index (Böckenholt & Hynan, 1994), which measures the degree to which information is processed vertically or horizontally (see Appendix 2 for more details about the SM measure). SM is computed as:

$$\mathrm{SM}=\frac{\sqrt{\mathrm{TR}}\left(\frac{\mathrm{JK}}{\mathrm{TR}}(\mathrm{TR}_J-\mathrm{TR}_K)-(K-J)\right)}{\sqrt{J^2(K-1)+\mathrm{K}^2(J-1)}} \qquad \text{(Eq. 3)}$$

Where (J) corresponds to the number of choice options (J=2), (K) the number of attributes (K=7), (TR) the total number of transitions, (TR_K) the number of attribute-wise transition and (TR_J) the number of option-wise transitions. The SM measure is zero for *random* search behaviour[2], negative for more attribute-wise (horizontal) transitions and positive for more option-wise (vertical) transitions. We compute the SM index for each participant (n) and choice task (t). The square root of the absolute value of the SM index for each participant (n) and choice task (t) was then modelled in a mixed effects linear regression model:

$$\sqrt{|\mathrm{SM_{nt}}|} = \beta_0 + \beta_1\mathrm{TRIAL_{nt}} + \beta_2\mathrm{TRIAL_{nt}^2} + \beta_3\mathrm{DSD_{nt}} + \beta_4\mathrm{EXPERIMENT_{nt}} + \omega_\mathrm{n} + \varepsilon_\mathrm{nt} \qquad (4)$$

[2] SM does not evaluate the quality of information processing, but only how the information is being visually processed. Thus, a “random search” (SM=0) does not necessarily imply *poor* decision making.

Where (ω) measures between-subjects variance, accounting for panel nature of the data. Modelling the absolute value of SM index allows investigation into deviations from *random* information processing (i.e., SM = 0).

On the basis of the theory by DeShazo and Fermo (2002) that participants to a CE allocate their limited attention in a rationally-adaptive manner, we predict that over the course of the experiment, when fatigue sets in, participants' choices become more random (i.e., the absolute value of SM will reduce). For task difficulty, fixation patterns could become more structured (i.e., the absolute value of SM increases). The order of the attributes and choice options (EXPERIMENT) may also influence the absolute value of SM, but the direction of the effect is more difficult to predict.

For the entire data set, a negative value for SM is obtained in 621 (89.2 %) cases, indicating attribute-wise (horizontal) information processing. Regression results, shown in Table 3, confirm our predictions. The direction of eye movements becomes more random over the course of the experiment (negative effect of TRIAL), but more structured for more difficult choices (positive effect of DSD) and more structured when COST is presented at the top (positive effect of EXPERIMENT).

5. VISUAL ATTENTION AND CHOICE BEHAVIOUR

Finally we examine how transitions (as measured by the SM variable) are linked to choice. Previous studies have shown that attribute non-attendance (or more generally attributes attention) is linked to eye movements during the choice (Balcombe et al, 2015; Krucien et al, 2017; Spinks & Mortimer, 2015). By examining how transitions are linked to choices, we can test the prediction of random regret minimisation (RRM) (Chorus et al, 2008; Chorus, 2010; Chorus, 2012; de Bekker-Grob & Chorus, 2013; Boeri et al, 2013) that multi-attribute information is processed on an attribute basis. In comparison, random utility maximisation (RUM) does not impose a particular type of information processing. Thus:

Random Utility Maximisation (RUM)

$$\mathrm{UTILITY}_{ntA} = \left(\textstyle\sum_k \beta_k X_{ntAk}\right) + \varepsilon_{ntA} \qquad (7)$$

$$\mathrm{UTILITY}_{ntB} = \left(\textstyle\sum_k \beta_k X_{ntBk}\right) + \varepsilon_{ntB} \qquad (8)$$

$$P(Y_{nt}=A)=P(U_{ntA}>U_{ntB})=P(V_{ntA} - V_{ntB} > \varepsilon_{ntB} - \varepsilon_{ntA}) \qquad (9)$$

$$\mathrm{DIFFERENCE}_{\mathrm{UTILITY}_{nt}} = \left(\textstyle\sum_k \beta_k (X_{ntAk} - X_{ntBk})\right) + \varepsilon_{nt} \qquad (10)$$

Random Regret Minimisation (RRM)

$$\mathrm{REGRET}_{ntA} = \left[\textstyle\sum_k \ln\left(1 + \exp\left(\beta_k\left(X_{ntB(k)} - X_{ntA(k)}\right)\right)\right)\right]^{\alpha} + \varepsilon_{ntA} \qquad (11)$$

$$\mathrm{REGRET}_{ntB} = \left[\sum_k \ln\left(1 + \exp\left(\beta_k\left(X_{ntA(k)} - X_{ntB(k)}\right)\right)\right)\right]^{\alpha} + \varepsilon_{ntB} \qquad (12)$$

Where (n) denotes the respondents, (t) the choice tasks, (k) the attributes, and (X) the value of the attributes. The (β) parameters represent preferences for attributes. The (ε) errors are assumed to be independently and identically distributed as type I extreme value leading to the multinomial logit (MNL) model (McFadden, 1974; Train, 2009).

Because very few opt-out responses were given[3], we only consider responses for either choice A or B, meaning that the REGRET function (Eq. 11, 12) collapses into the standard UTILITY function (Eq. 7, 8) when $\alpha = 1$. We investigate the impact of visual attention on participants' choices by specifying the (α) parameter as a function of the SM index:

$$\alpha = \exp\left(\alpha_1 \mathrm{SM^+}_{nt} + \alpha_2 \mathrm{SM^+}^2_{nt} + \alpha_3 \mathrm{SM^-}_{nt} + \alpha_4 \mathrm{SM^-}^2_{nt}\right) \qquad (13)$$

Where (SM^+) and (SM^-) correspond to the positive and negative portions of the SM index respectively. A negative SM (SM^-) indicates a tendency to process information on an attribute basis whilst a positive SM (SM+) corresponds to a vertical information processing. We expect (α_1) to be non-significant (H1: $\alpha_1 = 0$), because vertical information processing makes RUM and RRM more alike ($\alpha_1 \approx 0 \rightarrow \alpha \approx 1$). We expect ($\alpha_3$) to be significant (H2: $\alpha_3 \neq 0$) as attribute-wise information processing would be better captured by RRM than RUM.

The results are presented in Table 4. The RRM model provides a better account of participants' choices, as indicated by the lower log-likelihood (LL) value ($LL_{RRM} = 343.7$ vs. $LL_{RUM} = 346.1$). However this improvement does not reach significance at 5% level (LR test: Deviance = 4.88; P = 0.3). As expected (SM^-) has a significant and negative effect, indicating that when information processing became more attribute-wise, the RUM and RRM provide a different account of participants' choices.

6. DISCUSSION

In the present work, we show that eye-tracking can aid the understanding of information processing strategies in multi-attribute choice. Our results have important implications for the design and modelling

[3] The initial sample included 58 participants who provided 696 observations. The opt-out option was selected in only 48 (6.9 %) cases. For 53 (91.4 %) participants the share of opt-out choices was below 25% (i.e., less than three choices). The highest proportion of opt-out choices (i.e., 58.3 %) was attained by two (3.4 %) participants. After removing opt-out choices, 648 (93.1 %) observations remained.

of CEs, thus improving the validity of resulting policy recommendations. We found a range of visual biases that agree with earlier reported choice biases, including a left-to-right, top-to-bottom and first to last. Our work suggests that many of these biases originate in the deployment of visual attention during a CE. Importantly, these biases indicate that CE data can be substantially improved by randomising the order of alternatives, attributes and choice trials. While pen-and-paper randomisation may be complicated (although not impossible on a participant by participant basis), an increased reliance on computerized CEs (e.g., presented on a computer tablet or online via a web-browser) will facilitate such randomisation. Our analyses also demonstrate effects of task factors, including whether attributes are defined as best or worse, the level of complexity of the choice task, and ordering of attributes. Our data also showed that the RRM model outperformed the RUM model in linking eye movements with respondents' choice behaviour, although the exact link between eye movements and choice behaviour needs to be established in future research.

Because CEs contain words (besides numerical information), this raises the question to what extent factors that influence reading also influence eye movements when completing a CE. For reading, it is known that fixation durations are longer for less frequent (familiar) words, less predictable words, and for words with multiple meanings (Rayner, 1998). The extent to which these factors influence fixation times during CEs is unclear. In comparison to normal text, text in CEs is repeated often, which increases the predictability of the words. It is therefore likely that participants do not read all of the words of boxes containing longer text (the resolution of the eye tracker used, may not suffice to answer this question with sufficient confidence). Furthermore, we included two warm-up trials, which is expected to increase predictability further. In all, we therefore do not expect strong effects of word properties on processing a CE. A second possible factor involves reading ability of our participants. While we did not test explicitly for this, our participant groups were uniform on a broad range of other factors (all current or former students). Moreover, most of the effects tested in our study involved within subjects comparisons (the only exception being the EXPERIMENT factor), which are less likely to be influenced by individual differences.

There are a few possible limitations to our study. Firstly, the act of eye tracking may influence visual attention. This, however, is unlikely to influence the present results. While studies in social attention suggest that awareness of the recording of eye movements influences the direction of visual attention (Risko & Kingstone, 2011), these results are for objects that are socially less acceptable to be gazed at (e.g., a swimsuit calendar on the wall). No eye tracker bias is found for neutral objects.

Second, and perhaps more notable, our eye-tracker used a chin-and-forehead rest. The use of such equipment is not uncommon in eye tracking studies, particularly those requiring high spatial accuracy of the recordings (as in studies of reading); Rayner, 1978, 1998). The restriction of head movements, however, may have reduced the frequency of looking away from the text. Examining the effects of head restriction would be an interesting venue for future research, particularly now that mobile eye tracking technology is becoming more mainstream and more accurate.

Third, our sample, psychology students, was not representative of the UK population. The use of a student sample is in line with many studies in consumer research and social psychology (Henry, 2008), mostly because they are easier to recruit for lab based studies. There are indications that students may not be representative of the general population, as they tend to have stronger cognitive skills and show more compliant behaviour (Peterson & Merunka, 2014). Thus, the generalisability of our findings is limited. However, while choices may differ for a different population, there are no clear reasons to believe that the link between visual attention and choices and visual biases will depend on the population studied. With the development of more portable eye tracking equipment (e.g., EyeTribe, Eyelink Portable Duo, SMI Red250 Portable, Tobii X2-60, Tobii 2 Glasses, SMI Glasses, Positive Science eye tracker), future research should aim to move the work to a broader population based sample, and move from the laboratory into clinical and community settings.

Finally, we note that in our multivariate analysis of fixation times we investigated whether “better” attributes attract more attention (and conversely “worse” attribute less attention). While for the quantitative attributes (e.g., reduction of risk of hypertension) it is clear what defined “better”, we had to base our assumptions regarding best and worst levels on responses to the original CE, generated from the general population. Whether these extend to our student population needs to be addressed in future research.

7. Concluding remarks

Our study shows how eye tracking provides insight into how respondents complete CEs, suggesting a number of biases and context related decision strategies. As well as providing guidance to CE practitioners on the design and analysis of CE data, we hope our paper stimulates discussion of the use of eye-tracking in applied economic research. As Lahey & Oxley (2016) comment, research with an eye tracker is limited only by our imagination.

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References

Balcombe, Kelvin, Iain Fraser, and Eugene McSorley. 2015. “Visual Attention and Attribute Attendance in Multi-Attribute Choice Experiments: DISCRETE-CHOICE EXPERIMENTS AND EYE-TRACKING.” *Journal of Applied Econometrics* 30 (3): 447–67. doi:10.1002/jae.2383.

Bateman, Ian J., Diane Burgess, W. George Hutchinson, and David I. Matthews. 2008. “Learning Design Contingent Valuation (LDCV): NOAA Guidelines, Preference Learning and Coherent Arbitrariness.” *Journal of Environmental Economics and Management* 55 (2): 127–41. doi:10.1016/j.jeem.2007.08.003.

Bekker-Grob, Esther W. de, Mandy Ryan, and Karen Gerard. 2012. “Discrete Choice Experiments in Health Economics: A Review of the Literature.” *Health Economics* 21 (2): 145–72. doi:10.1002/hec.1697.

Belle, Goedele van. 2010. “Fixation Patterns during Recognition of Personally Familiar and Unfamiliar Faces.” *Frontiers in Psychology*. doi:10.3389/fpsyg.2010.00020.

Butler, S., I.D. Gilchrist, D.M. Burt, D.I. Perrett, E. Jones, and M. Harvey. 2005. “Are the Perceptual Biases Found in Chimeric Face Processing Reflected in Eye-Movement Patterns?” *Neuropsychologia* 43 (1): 52–59. doi:10.1016/j.neuropsychologia.2004.06.005.

Campbell, Danny, David A. Hensher, and Riccardo Scarpa. 2011. “Non-Attendance to Attributes in Environmental Choice Analysis: A Latent Class Specification.” *Journal of Environmental Planning and Management* 54 (8): 1061–76. doi:10.1080/09640568.2010.549367.

Caplin, Andrew, and Mark Dean. 2008. “Economic Insights from ‘Neuroeconomic’ Data.” *American Economic Review* 98 (2): 169–74. doi:10.1257/aer.98.2.169.

Clark, Michael D., Domino Determann, Stavros Petrou, Domenico Moro, and Esther W. de Bekker-Grob. 2014. “Discrete Choice Experiments in Health Economics: A Review of the Literature.” *PharmacoEconomics* 32 (9): 883–902. doi:10.1007/s40273-014-0170-x.

Day, Brett, Ian J. Bateman, Richard T. Carson, Diane Dupont, Jordan J. Louviere, Sanae Morimoto, Riccardo Scarpa, and Paul Wang. 2012. “Ordering Effects and Choice Set Awareness in Repeat-Response Stated Preference Studies.” *Journal of Environmental Economics and Management* 63 (1): 73–91. doi:10.1016/j.jeem.2011.09.001.

Day, Brett, and Jose-Luis Pinto Prades. 2010. “Ordering Anomalies in Choice Experiments.” *Journal of Environmental Economics and Management* 59 (3): 271–85. doi:10.1016/j.jeem.2010.03.001.

DeShazo, J.R., and German Fermo. 2002. “Designing Choice Sets for Stated Preference Methods: The Effects of Complexity on Choice Consistency.” *Journal of Environmental Economics and Management* 44 (1): 123–43. doi:10.1006/jeem.2001.1199.

Duchowski, Andrew T. 2007. *Eye Tracking Methodology: Theory and Practice*. 2nd ed. London: Springer.

Durgin, Frank H., Erika Doyle, and Louisa Egan. 2008. “Upper-Left Gaze Bias Reveals Competing Search Strategies in a Reverse Stroop Task.” *Acta Psychologica* 127 (2): 428–48. doi:10.1016/j.actpsy.2007.08.007.

Everdell, Ian T, Heidi Marsh, Micheal D Yurick, Kevin G Munhall, and Martin Par? 2007. “Gaze Behaviour in Audiovisual Speech Perception: Asymmetrical Distribution of Face-Directed Fixations.” *Perception* 36 (10): 1535–45. doi:10.1068/p5852.

Flynn, Terry N., Marcel Bilger, Chetna Malhotra, and Eric A. Finkelstein. 2016. “Are Efficient Designs Used in Discrete Choice Experiments Too Difficult for Some Respondents? A Case Study Eliciting Preferences for End-of-Life Care.” *PharmacoEconomics* 34 (3): 273–84. doi:10.1007/s40273-015-0338-z.

Foulsham, Tom, Joey T. Cheng, Jessica L. Tracy, Joseph Henrich, and Alan Kingstone. 2010. “Gaze Allocation in a Dynamic Situation: Effects of Social Status and Speaking.” *Cognition* 117 (3): 319–31. doi:10.1016/j.cognition.2010.09.003.

Gigerenzer, Gerd, and Peter M. Todd. 2001. *Simple Heuristics That Make Us Smart*. 1. issued as an Oxford Univ. Press paperback. Evolution and Cognition. Oxford: Oxford Univ. Press.

Guo, Kun, Kerstin Meints, Charlotte Hall, Sophie Hall, and Daniel Mills. 2009. “Left Gaze Bias in Humans, Rhesus Monkeys and Domestic Dogs.” *Animal Cognition* 12 (3): 409–18. doi:10.1007/s10071-008-0199-3.

Hensher, David A., Andrew T. Collins, and William H. Greene. 2013. “Accounting for Attribute Non-Attendance and Common-Metric Aggregation in a Probabilistic Decision Process Mixed Multinomial Logit Model: A Warning on Potential Confounding.” *Transportation* 40 (5): 1003–20. doi:10.1007/s11116-012-9447-0.

Hess, Stephane, Amanda Stathopoulos, Danny Campbell, Vikki O’Neill, and Sebastian Caussade. 2013. “It’s Not That I Don’t Care, I Just Don’t Care Very Much: Confounding between Attribute Non-Attendance and Taste Heterogeneity.” *Transportation* 40 (3): 583–607. doi:10.1007/s11116-012-9438-1.

Hole, Arne Risa. 2011. “A Discrete Choice Model with Endogenous Attribute Attendance.” *Economics Letters* 110 (3): 203–5. doi:10.1016/j.econlet.2010.11.033.

Hole, Arne Risa, Julie Riise Kolstad, and Dorte Gyrd-Hansen. 2013. “Inferred vs. Stated Attribute Non-Attendance in Choice Experiments: A Study of Doctors? Prescription Behaviour.” *Journal of Economic Behavior & Organization* 96 (December): 21–31. doi:10.1016/j.jebo.2013.09.009.

Holmqvist, Kenneth, ed. 2011. *Eye Tracking: A Comprehensive Guide to Methods and Measures*. Oxford ; New York: Oxford University Press.

Kahneman, Daniel, Jack L Knetsch, and Richard H Thaler. 1991. “Anomalies: The Endowment Effect, Loss Aversion, and Status Quo Bias.” *Journal of Economic Perspectives* 5 (1): 193–206. doi:10.1257/jep.5.1.193.

Karmarkar, Uma R., Baba Shiv, and Brian Knutson. 2015. “Cost Conscious? The Neural and Behavioral Impact of Price Primacy on Decision Making.” *Journal of Marketing Research* 52 (4): 467–81. doi:10.1509/jmr.13.0488.

Kjær, Trine, Mickael Bech, Dorte Gyrd-Hansen, and Kristian Hart-Hansen. 2006. “Ordering Effect and Price Sensitivity in Discrete Choice Experiments: Need We Worry?” *Health Economics* 15 (11): 1217–28. doi:10.1002/hec.1117.

Knoepfle, Daniel T., Joseph Tao-yi Wang, and Colin F. Camerer. 2009. “Studying Learning in Games Using Eye-Tracking.” *Journal of the European Economic Association* 7 (2–3): 388–98. doi:10.1162/JEEA.2009.7.2-3.388.

Krucien, Nicolas, Mandy Ryan, and Frouke Hermens. 2017. “Visual Attention in Multi-Attributes Choices: What Can Eye-Tracking Tell Us?” *Journal of Economic Behavior & Organization* 135 (March): 251–67. doi:10.1016/j.jebo.2017.01.018.

Lahey, Joanna N., and Douglas Oxley. 2016. “The Power of Eye Tracking in Economics Experiments.” *American Economic Review* 106 (5): 309–13. doi:10.1257/aer.p20161009.

Manski, Charles F. 1977. “The Structure of Random Utility Models.” *Theory and Decision* 8 (3): 229–54. doi:10.1007/BF00133443.

Mantonakis, Antonia, Pauline Rodero, Isabelle Lesschaeve, and Reid Hastie. 2009. “Order in Choice: Effects of Serial Position on Preferences.” *Psychological Science* 20 (11): 1309–12. doi:10.1111/j.1467-9280.2009.02453.x.

McFadden, Daniel. 1974. “Conditional Logit Analysis of Qualitative Choice Behavior.” In *FRONTIERS IN ECONOMETRICS*, P. Zarembka, 105–42. New York: Academic Press.

McIntosh, E., and M. Ryan. 2002. “Using Discrete Choice Experiments to Derive Welfare Estimates for the Provision of Elective Surgery: Implications of Discontinuous Preferences.” *Journal of Economic Psychology* 23 (3): 367–82. doi:10.1016/S0167-4870(02)00081-8.

McNair, Ben J., David A. Hensher, and Jeff Bennett. 2012. “Modelling Heterogeneity in Response Behaviour Towards a Sequence of Discrete Choice Questions: A Probabilistic Decision Process Model.” *Environmental and Resource Economics* 51 (4): 599–616. doi:10.1007/s10640-011-9514-6.

Meibner, Martin, Andres Musalem, and Joel Huber. 2016. “Eye Tracking Reveals Processes That Enable Conjoint Choices to Become Increasingly Efficient with Practice.” *Journal of Marketing Research* 53 (1): 1–17. doi:10.1509/jmr.13.0467.

Payne, John W., James R. Bettman, and Eric J. Johnson. 1993. *The Adaptive Decision Maker*. Cambridge ; New York, NY, USA: Cambridge University Press.

Rayner, K. 1978. “Eye Movements in Reading and Information Processing.” *Psychological Bulletin* 85 (3): 618–60.

———. 1998. “Eye Movements in Reading and Information Processing: 20 Years of Research.” *Psychological Bulletin* 124 (3): 372–422.

Reutskaja, Elena, Rosemarie Nagel, Colin F Camerer, and Antonio Rangel. 2011. “Search Dynamics in Consumer Choice under Time Pressure: An Eye-Tracking Study.” *American Economic Review* 101 (2): 900–926. doi:10.1257/aer.101.2.900.

Rosenberger, Randall S., George L. Peterson, Andrea Clarke, and Thomas C. Brown. 2003. “Measuring Dispositions for Lexicographic Preferences of Environmental Goods: Integrating Economics, Psychology and Ethics.” *Ecological Economics* 44 (1): 63–76. doi:10.1016/S0921-8009(02)00221-5.

Ryan, Mandy, Deokhee Yi, Alison Avenell, Flora Douglas, Lorna Aucott, Edwin van Teijlingen, and Luke Vale. 2015. “Gaining Pounds by Losing Pounds: Preferences for Lifestyle Interventions to Reduce Obesity.” *Health Economics, Policy and Law* 10 (2): 161–82. doi:10.1017/S1744133114000413.

Saelensminde, Kjartan. 2006. “Causes and Consequences of Lexicographic Choices in Stated Choice Studies.” *Ecological Economics* 59 (3): 331–40. doi:10.1016/j.ecolecon.2005.11.001.

Scarpa, R., R. Zanoli, V. Bruschi, and S. Naspetti. 2013. “Inferred and Stated Attribute Non-Attendance in Food Choice Experiments.” *American Journal of Agricultural Economics* 95 (1): 165–80. doi:10.1093/ajae/aas073.

Scott, Anthony, and Sandra Vick. 1999. “Patients, Doctors and Contracts: An Application of Principal-Agent Theory to the Doctor-Patient Relationship.” *Scottish Journal of Political Economy* 46 (2): 111–34. doi:10.1111/1467-9485.00124.

Shimojo, Shinsuke, Claudiu Simion, Eiko Shimojo, and Christian Scheier. 2003. “Gaze Bias Both Reflects and Influences Preference.” *Nature Neuroscience* 6 (12): 1317–22. doi:10.1038/nn1150.

Shugan, Steven M. 1980. “The Cost of Thinking.” *Journal of Consumer Research* 7 (2): 99. doi:10.1086/208799.

Spinks, Jean, and Duncan Mortimer. 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 (1). doi:10.1186/s12911-016-0251-1.

Tatler, Benjamin W., Roland J. Baddeley, and Benjamin T. Vincent. 2006. “The Long and the Short of It: Spatial Statistics at Fixation Vary with Saccade Amplitude and Task.” *Vision Research* 46 (12): 1857–62. doi:10.1016/j.visres.2005.12.005.

Train, Kenneth. 2009. *Discrete Choice Methods with Simulation*. 2nd ed. Cambridge ; New York: Cambridge University Press.

Uggeldahl, Kennet, Catrine Jacobsen, Thomas Hedemark Lundhede, and S?ren B?ye Olsen. 2016. “Choice Certainty in Discrete Choice Experiments: Will Eye Tracking Provide Useful Measures?” *Journal of Choice Modelling* 20 (September): 35–48. doi:10.1016/j.jocm.2016.09.002.

Van Loo, Ellen J., Vincenzina Caputo, Rodolfo M. Nayga, Han-Seok Seo, Baoyue Zhang, and Wim Verbeke. 2015. “Sustainability Labels on Coffee: Consumer Preferences, Willingness-to-Pay and Visual Attention to Attributes.” *Ecological Economics* 118 (October): 215–25. doi:10.1016/j.ecolecon.2015.07.011.

Viney, Rosalie, Elizabeth Savage, and Jordan Louviere. 2005. “Empirical Investigation of Experimental Design Properties of Discrete Choice Experiments in Health Care.” *Health Economics* 14 (4): 349–62. doi:10.1002/hec.981.

Wang, Joseph Tao-yi, Michael Spezio, and Colin F Camerer. 2010. “Pinocchio’s Pupil: Using Eyetracking and Pupil Dilation to Understand Truth Telling and Deception in Sender-Receiver Games.” *American Economic Review* 100 (3): 984–1007. doi:10.1257/aer.100.3.984.

Table 1. Attributes and levels used to define the health and lifestyle (H&L) programmes

Programme attributes*	Level 1 [WORST**]	Level 2 [INTERMEDIATE**]	Level 3 [INTERMEDIATE**]	Level 4 [BEST**]	Coding***	Expected effect****
Comprehensiveness [PROGRAMME]	Partial (Healthy eating OR Physical activity OR Healthy eating with support for management of weight changes OR Physical activity with support for management of weight changes)	-	-	Full (Healthy eating and physical activity OR Healthy eating and physical activity with support for management of weight changes)	Dummy (Ref: Partial)	^{3} 0
Goal [GOAL]	Partial (Feeling better OR Looking better)	-	-	Full (Looking better and feeling better)	Dummy (Ref: Partial)	^{3} 0
Weight reduction [WEIGHT]	Stay the same	Lose half a stone	Lose a stone	Lose one and half stone	Continuous (0; 0.5; 1; 1.5)	^{3} 0
Reduction in risk of Diabetes [DIABETES]	No reduction	Reducing risk up to 20%	Reducing risk by 20-40%	Reducing risk by 40-60%	Continuous (0; 20; 40; 60)	^{3} 0
Reduction in risk of high blood pressure [HBP]	No reduction	Reducing risk up to 25%	Reducing risk by 25-50%	Reducing risk by 50-75%	Continuous (0; 25; 50; 75)	^{3} 0
Time per day [TIME]	120 min/day	90 min/day	60 min/day	30 min/day	Continuous (30; 60; 90; 120)	£ 0
Cost per week [COST]	£20/week	£10/week	£5/week	£1/week	Continuous (1; 5; 10; 20)	£ 0

* *Attributes are listed by order of appearance in the choice options (i.e., PROGRAMME was located at the top of the options)*

** *WORST/INTERMEDIATE/BEST indicate whether the attribute level was set at its worst/intermediate/best theoretical value (given expected preferences)*

*** *CODING indicates how the attributes were included in the modelling of participants' choices*

**** *EXPECTED EFFECT refers to the average preferences for the attribute*

Table 2. Mixed effects regression of ln(fixation times)

	MLE	SE	P
1. Model parameters			
Constant	6.204	0.063	< 0.001
LEFT	0.146	0.015	< 0.001
POSITION (Top)	0.259	0.018	< 0.001
POSITION (Bottom)	-0.170	0.019	< 0.001
LEVEL (Best)	0.090	0.021	< 0.001
LEVEL (Worst)	-0.037	0.017	0.026
TRIAL	-0.039	0.009	< 0.001
TRIAL x TRIAL	0.002	0.001	< 0.001
DIFFICULTY (DSD)	0.336	0.091	< 0.001
EXPERIMENT	0.182	0.071	0.010
Individual errors	0.264	-	-
Observation errors	0.680	-	-
2. Model statistics			
# Observations		8,421	
# Parameters		11	
Log-likelihood		8,816.8	

MLE: Maximum Likelihood Estimate; SE: Standard Error;
P: P-value; DSD = Dispersion of standard deviation

Table 3. Mixed effects regression of SM index

	MLE	SE	P
1. Model parameters			
Constant	1.501	0.089	< 0.001
TRIAL	-0.038	0.017	0.026
TRIAL x TRIAL	0.001	0.001	0.652
DIFFICULTY (DSD)	0.020	0.165	0.905
EXPERIMENT	0.381	0.093	< 0.001
Individual error	0.338	-	-
Observation error	0.356	-	-
2. Model statistics			
# Observations		696	
# Parameters		6	
Log-likelihood		352.3	

MLE: Maximum Likelihood Estimate; SE: Standard Error; P: P-value

Table 4. MNL modelling of discrete choices with RUM and RRM approaches

	RUM			RRM		
	MLE	**SE**	**P**	**MLE**	**SE**	**P**
1. Model parameters						
PROGRAMME	0.624	0.234	0.008	0.606	0.232	0.009
GOAL	0.885	0.183	< 0.001	0.891	0.181	< 0.001
WEIGHT	0.490	0.155	0.002	0.526	0.156	< 0.001
DIABETES	0.024	0.004	< 0.001	0.024	0.004	< 0.001
HBP	0.011	0.003	< 0.001	0.011	0.003	< 0.001
TIME	-0.015	0.002	< 0.001	-0.015	0.002	< 0.001
COST	-0.029	0.011	0.009	-0.028	0.011	0.011
Regret (α1)	-	-	-	0.360	0.331	0.277
Regret (α2)	-	-	-	-0.115	0.190	0.547
Regret (α3)	-	-	-	-0.135	0.069	0.049
Regret (α4)	-	-	-	-0.016	0.011	0.129
2. Model statistics						
# Observations		648			648	
# Parameters		7			11	
Log-likelihood		346.1			343.7	

MLE: Maximum Likelihood Estimate; SE: Standard Error; P: P-value

Figure 1. Illustration of the choice tasks and regions of interest (ROI) mapping*

Lifestyle	1	Lifestyle A	9	Lifestyle B	17
The programme	2	Healthy eating and physical activity	10	Physical activity	18
Weight change in 2 years	3	Lose half a stone	11	Lose a stone	19
Short term goals	4	Feeling better	12	Looking better	20
Reduction in risk of type II diabetes	5	Reducing risk by 20-40%	13	No reduction	21
Reduction in risk of high blood pressure	6	No reduction	14	Reducing risk up to 25%	22
Time per day	7	90 min/day	15	30 min/day	23
Costs per week	8	£5/week	16	£20/week	24

** Dashes squares indicate the ROI and were not showed to the subjects during the experiment*

Figure 2. Evolution of information processing strategies (IPS) over (fixation) time