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Elimination and selection by aspects in health choice experiments: Prioritising health service innovations[☆]

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Seda Erdem[*], Danny Campbell[†], and Carl Thompson[‡]

Abstract

Priorities for public health innovations are typically not considered equally by all members of the public. When faced with a choice between various innovation options, it is, therefore, possible that some respondents eliminate and/or select innovations based on certain characteristics. This paper proposes a flexible method for exploring and accommodating situations where respondents exhibit such behaviours, whilst addressing preference heterogeneity. We present an empirical case study on the public's preferences for health service innovations. We show that allowing for elimination-by-aspects and/or selection-by-aspects behavioural rules leads to substantial improvements in model fit and, importantly, has implications for willingness to pay estimates and scenario analysis.

Keywords: Discrete Choice Experiments; elimination by aspects; selection by aspects; latent class logit model; health service innovations.

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[*]Corresponding author.
Economics Division, Stirling Management School, University of Stirling, UK. Tel: (44) 0 1786 46 7478. E-mail:seda.erdem@stir.ac.uk

[†]Economics Division, Stirling Management School, University of Stirling, UK. E-mail: danny.campbell@stir.ac.uk

[‡]Department of Health Sciences, University of York, UK. E-mail:carl.thompson@york.ac.uk

1. Introduction

Prioritisation of health service innovations in a health care system where the number of new practices, services and technologies outstrips scarce resources is inevitable. Policy-makers and other decision-makers in the health care system use various methods to inform decisions about which innovation(s) to invest in. Alongside the use of economic criteria, including cost-effectiveness and cost-utility, other factors (e.g., ease of implementation, severity and burden of disease, age of target group) are used in the prioritisation of health service innovations (Boote et al., 2010; The King's Fund, 2010; Barber et al., 2011). Recently, national agencies have sought to incorporate public preferences in priority setting and investment decisions (e.g., UK House of Commons, 2012; Health Canada, 2005).

Both moral and political arguments can be advanced in support of public involvement (Thompson et al., 2009; Boote et al., 2010). Where healthcare is funded though taxation (e.g., as in the case of UK) the public effectively become "part-owner" and so the system has a tacit moral duty to involve them in decisions that impact on their health status (Dyer, 2004; O'Donnell and Entwistle, 2004). Politically, public involvement provides a voice for disadvantaged social groups (Beresford, 2005; Boote et al., 2010) as well as a more democratic decision-making process with greater accountability (Florin and Dixon, 2004). Furthermore, public involvement can increase the relevance, appropriateness and quality of health and social care research (Cotterell, 2007; Cashman et al., 2008).

There are various methods used for the prioritisation of health service innovations, such as cost-effectiveness, cost-utility, cost-benefit. Despite the appeal of these methods, they are often unable to uncover priorities from a societal perspective (Mirelman et al., 2012). Discrete choice experiments (DCEs), which is a preference elicitation method, are particularly well suited for identifying the health service innovations that are deemed preferable from the public's point of view. They have been used widely to elicit public and patient preferences in health economics research (see de Bekker-Grob et al., 2012, for a review). In addition, the choice experiments have also been used by the UK NICE Decision Support Unit (**?**), as well as other policy relevant researches funded by the UK government bodies (Torbica et al., 2014; Gerard et al., 2012; Ryan et al., 2001; Cairns and Van der Pol, 2000).

Unlike decision-making techniques based on a single criterion (e.g., cost-benefit analysis), DCEs utilise a multi-criteria approach to inform prioritisation decisions from a broader context. It involves decomposing health service innovations into their characteristics (or decision criteria), such as their cost, how long they take to implement, and their potential impact on public health. Viewing innovations as 'bundles' of their characteristics (or attributes) allows us to study a wide range of innovations sharing the same characteristics (e.g., cost), but at different levels (e.g., £10, £20). The DCE then involves asking individuals to choose those innovations they would most like to see their healthcare system invest in from the comparisons offered to them. In this way, individuals 'trade-off' the various attributes of health service innovations. This generates outputs to weigh and compare competing innovation scenarios, importances and acceptability of decision criteria used in prioritisation from the public's perspective.

Notwithstanding the appeal of DCEs, and its use in various fields, including health economics (e.g., see Green and Gerard, 2009; Guo et al., 2011; de Bekker-Grob et al., 2012, for recent applications), there are some issues raised in the literature that might be important. For example, in DCE studies,the typical assumption that individuals consider and trade-off between all attributes within the choice sets is often questioned. Indeed, a number of studies (e.g., Hensher, 2006; Carlsson et al., 2010; Campbell et al., 2011; Hensher et al., 2012; Scarpa et al., 2013) show that many respondents exhibit signs of adopting a range of simplifying mental processing rules, which are referred to as decision-making heuristics (Gigerenzer and Gaissmaier, 2011). For example, a large body of research (e.g., see Hensher et al., 2005; Campbell et al., 2008; Ryan et al., 2009; Campbell et al., 2011; Hole et al., 2013; Lagarde, 2012; Scarpa et al., 2013; Erdem et al., 2014) has shown that many respondents simplify their choice by ignoring (or not considering) some attributes of the DCE (i.e.,'attribute non-attendance'), or make their decision based on certain criteria, such as the cost thresholds (e.g., Campbell et al., 2012, 2014). Other processing strategies may consist of respondents eliminating or selecting some alternatives based on some decision criteria. Respectively, these are referred to as 'elimination-by-aspects' (EBA) and 'selection-by-aspects' (SBA). A number of factors may contribute to these behaviours, including: a genuine disinterest or interest in the attribute; the context and survey design related issues, such as complexity, controversy and sensitivity of the survey topic, irrelevance or relevance of the attribute to respondents, cognitive demand required to complete choice tasks; respondents' different capabilities and motivations (Hensher et al., 2005); or strategic behaviour respondents may exhibit, especially in public policy choices, such as innovation prioritisation in a publicly-funded healthcare system.

Despite the increased attention on decision-making heuristics within the stated preference literature, with the exception of a few studies (e.g., Batley and Daly, 2012; Hess and Stathopoulos, 2012; Campbell et al., 2014), EBA and SBA behaviours have largely been overlooked. This paper furthers this line of enquiry and explores EBA and SBA behaviours in the context of public preferences for health service innovations. To do this we use empirical data obtained from a DCE survey administered in the UK exploring public preferences relating to health service innovation investment decisions. Accounting for EBA and SBA behaviours may be particularly important in such a context since priorities for public health investment may not be considered equally by all members of the public. For example, within the UK the clinical guidelines for obesity, which is one of the health problems receiving increased attention, recommend that "managers and health professionals in all primary care settings should ensure that preventing and managing obesity is a priority, at both strategic and delivery levels, and dedicated resources should be allocated for action" (NICE, 2006, p.7). This policy priority is not always given the same weight by the public. Indeed, some members of the public consider obesity as being "self-inflicted" and dislike spending on treatments targeting people with obesity (e.g., Lund et al., 2011), whereas others recognise that obesity is not necessarily merely a lifestyle choice and there should be equal health care access for those who are struggling with it (e.g., Chambers and Traill, 2011; Sikorski et al., 2012). In contrast, there may be situations where the public may want to prioritise innovations targeting patients with a certain illness (e.g., cancer patients), and thus, they may choose innovation investment options targeting these people (e.g., O'Shea et al., 2008).

Due to the range in views and priorities, at least in principle, one may postulate the hypothesis that there is likely to be a subset of respondents who systematically restricted their actual choice set to only include alternatives that ensured certain population groups would be targeted. In fact, it is possible that some respondents selected their preferred innovation alternatives based solely on a specific target group. This may then imply that individuals eliminated or selected alternatives successively, on the basis of their failure to possess certain attributes. Failing to account for this type of processing strategy is likely to be suboptimal.

In this paper, we investigate respondents' decision-making strategies based on who the health service innovations are mostly intended for. Specifically, we propose a flexible modelling approach that is capable of addressing EBA- and SBA-like choice behaviours, whilst addressing preference heterogeneity. We use the approach to investigate the extent to which respondents eliminated alternatives targeting certain populations or limited their choice to those alternatives that targeted a certain population. The approach used in the paper is intuitive as it provides probabilistic estimates of the proportion of the sample who are associated with each type of behaviour. We first analyse the data assuming the homogeneity of preferences and the use of the conventional random utility maximisation (RUM) individual behavioural rule. We then build on this by separately accommodating EBA- and SBA-like behaviours and subsequently for both type of behaviours concurrently. Finally, we estimate the same models, but where the heterogeneity in respondents' preferences is accounted for. Overall, our approach is clearly shown to help build a richer insight into respondent's behaviour as well as raise a number of concerns about the appropriateness of assuming the deterministic choice set, as generated by the experimental design. The empirical application of our modelling approach shows that it has important implications for model fit, welfare analysis and prediction.

This paper adds to the literature in a number of ways. It highlights the importance of and need for identifying decision-making heuristics respondents may adopt in choice experiments, along with preference heterogeneity. The method outlined in the paper provides a step forward on how to accommodate EBA- and SBA-like behaviours concurrently, along with preference heterogeneity, in choice experiments using flexible probabilistic choice models. In addition to this methodological contribution, the research presents a unique conceptual approach to exploring public's preferences for health service innovations, which allows policy-makers to compare numerous competing health service innovations.

The structure of this paper is as follows: Section 2 describes our modelling approach, Section 3 explains the survey design and introduces the data, Section 4 presents the results, and finally, Section 5 presents the conclusions.

2. Modelling approach

The analysis of the choice data is based on conventional RUM, where individuals are assumed to select the choice alternative that yields the greatest expected utility to them. The utility of the chosen alternative i for respondent n at a choice occasion t that is composed of attributes x can be written as:

$$U_{nit} = \beta x_{nit} + \varepsilon_{nit}, \tag{1}$$

where β represents the vector of parameters to be estimated, and ε is an *iid* type I extreme value (EV1) distributed error term, with constant variance of $\pi^2/6$. Given these assumptions, the probability of the choosing alternative i in choice occasion t can be expressed by a multinomial logit (MNL) model:

$$\Pr\left(i_{nt} | \beta, x_{nit}\right) = \frac{\exp\left(\beta x_{nit}\right)}{\sum_{j=1}^{J} \exp\left(\beta x_{njt}\right)}. \tag{2}$$

As respondents make a sequence of choices, the probability of this sequence can be written as:

$$\Pr\left(y_n | \beta, x_n\right) = \prod_{t=1}^{T_n} \Pr\left(i_{nt} | \beta, x_{nit}\right), \tag{3}$$

where y_n gives the sequence of choices over the T_n choice occasions for respondent n, i.e., $y_n = \langle i_{n1}, i_{n2}, \ldots, i_{nT_n} \rangle$.

While the MNL model expressed in Eq. (3) directly uncovers estimates of marginal utility for the various attributes, in the typical stated choice experiment it does so in a manner that assumes all respondents consider all offered alternatives, including those that are unacceptable to them. However, since respondents may restrict, for whatever reason[1], their actual consideration set may include only those alternatives that meet a specific condition, this assumption may not necessarily be appropriate (see Campbell et al., 2014, for a discussion).

[1]As stated earlier in the paper, this may be due to a number of factors (e.g., disinterest/interest, framing and design, complexity, motivations and irrelevance/relevance). Without additional in-depth follow-up questions it is difficult to establish the reasons why some respondents exclude certain alternatives from their consideration set. While uncovering this information would be useful, the approach set out here acknowledges the fact that such behaviours exist (regardless of the reasons) and accommodate them without the need to establish why they exist.

The following models presented in this section accommodate cases where some respondents may have rationally and systematically excluded some of the proposed alternatives from their consideration set at the moment of choice (i.e., EBA), and/or some make choices based on certain criteria, such as certain attributes or attribute levels (i.e., SBA). This is motivated by the fact that, failing to account for either EBA- or SBA-like processing strategies is likely to be suboptimal, and perhaps lead to misguided inferences, as the model does not reflect actual choice behaviour.

2.1. Accounting for EBA- and SBA-like choice behaviours

EBA, proposed by (Tversky, 1972a,b), assumes that some respondents may eliminate some of the alternatives from their choice sets that do not satisfy certain acceptability criteria (or fulfil a threshold value for an attribute), until a single 'chosen' alternative remains. SBA is an alternative model that retains the sequential nature of the EBA. In this case, the choice is based on the repetitive process of 'selection' of alternatives fulfilling the decision criteria, rather than making choices based on an elimination process. To account for these types of behaviours, the choice probability in Eq. 3 can be written in the following generalised form:

$$\Pr\left(y_n|\beta,\pi,x_n\right)=\sum_{c=1}^{C=4}\pi_c\prod_{t=1}^{T_n}\left(\Pr\left(i_{nt}|\beta,x_{nit}\right)\left(1-\psi_r I_{x_{knit}}^{\text{SBA}}\right)+\psi_r I_{x_{knit}}^{\text{SBA}}\right)\left(1-\psi_q I_{x_{knit}}^{\text{EBA}}\right), \tag{4}$$

where $I_{x_{knit}}^{\text{EBA}}$ and $I_{x_{knit}}^{\text{SBA}}$ are indicator variables denoting whether the level of an attribute k that is taken as decision 'criterion' for elimination (i.e., l_k^{EBA}) or selection (i.e., l_k^{SBA}) of alternatives, is present in alternative i in choice occasion t faced by respondent n:

$$I_{x_{knit}}^{\text{EBA}}=\begin{cases}1 & \text{if } x_{knit}=l_k^{\text{EBA}};\\ 0 & \text{otherwise.}\end{cases} \tag{5a}$$

$$I_{x_{knit}}^{\text{SBA}}=\begin{cases}1 & \text{if } x_{knit}=l_k^{\text{SBA}};\\ 0 & \text{otherwise.}\end{cases} \tag{5b}$$

ψ_r and ψ_q are discrete variables with possible values of 1 or 0, representing whether or not the respondents exhibited SBA- and EBA-like behaviours, respectively. There may be situations where respondents actually exhibit both choice behaviours. In such cases, not accommodating for both types of behaviours concurrently is likely to result in erroneous choice predictions and welfare estimates. To illustrate how both choice behaviours can occur simultaneously, consider a respondent possesses an extreme negative view towards an attribute level l_k^{EBA} and is opposed to it. In this case they are likely to eliminate choice alternatives that include this level. Suppose this respondent also holds an extreme positive view towards the attribute level l_k^{SBA} and always chooses among alternatives including this level, if it is present in their choice tasks. In Eq. 4, this is accounted by C which denotes the number of combinations of EBA- and SBA-like behaviours. In this case, $C = 4$:

$$C = \begin{cases} 1 \text{ in the case where } \psi_{q=0} \text{ and } \psi_{r=0}\text{; RUM behaviour} \\ 2 \text{ in the case where } \psi_{q=1} \text{ and } \psi_{r=0}\text{; EBA behaviour} \\ 3 \text{ in the case where } \psi_{q=0} \text{ and } \psi_{r=1}\text{; SBA behaviour} \\ 4 \text{ in the case where } \psi_{q=1} \text{ and } \psi_{r=1}\text{; EBA and SBA behaviours.} \end{cases} \tag{6}$$

In case 4 (i.e., where both ψ_q and ψ_r are equal to 1) the respondent exhibits both SBA and EBA behaviours across their sequence of choices.[2]

The alternatives taken into account by a respondent cannot be known with certainty. However, observed choice behaviour helps make probabilistic statements about the likelihood of competing consideration sets being the true choice set. Since a respondent's true consideration set cannot be known with certainty, this model assumes that the choice sets are latent. These (unconditional) probabilities are represented by π_c. For example, $\pi_{c=1}$, which is associated with $\psi_{q=0}$ and $\psi_{r=0}$, represents the (unconditional) probability that respondents do not show such processing strategies (in other words, the behaviour reflects RUM). We denote this probability as π_{RUM}. Similarly, we represent the probabilistic estimates for the three remaining individual behavioural rules by π_{EBA}, π_{SBA} and $\pi_{\text{EBA\&SBA}}$, which, respectively, relate to classes where only EBA-like behaviour is exhibited, only SBA-like behaviour is displayed, and, finally, where both EBA- and SBA-like behavioural rules are adopted. We then estimate these probabilities, along with the attribute parameters using maximum likelihood estimation procedure.

The expression presented in Eq. 4 is generalisable and can be reduced to accommodate EBA- or SBA-like behaviour alone. For example, in the case where ψ_q only takes the value zero—meaning that respondents do not eliminate the attribute l_k^{EBA} from their choice set—the expression investigates only SBA-like behaviour and can be expressed using the following simplified form:

$$\Pr\left(y_n|\beta,\pi,x_n\right) = \sum_{r=1}^{R=2} \pi_r \prod_{t=1}^{T_n} \Pr\left(i_{nt}|\beta,x_{nit}\right)\left(1-\psi_r I_{x_{knit}}^{\text{SBA}}\right) + \psi_r I_{x_{knit}}^{\text{SBA}}. \tag{7}$$

Under this framework, the probability of an alternative being chosen in cases where $I_{x_{knit}}^{\text{SBA}} = 1$ is one among respondents who exhibit SBA-like behaviour (i.e., $\Pr\left(i_{nt}|\beta,x_{nit}\right)\left(1-\psi_r I_{x_{knit}}^{\text{SBA}}\right) + \psi_r I_{x_{knit}}^{\text{SBA}} = 1$ when $\psi_{r=1}$). In all other situations the probability simplifies back to $\Pr\left(i_{nt}|\beta,x_{nit}\right)$ and can be obtained using the MNL model described in Eq. (3).

[2]Of course, we acknowledge that for a given choice task we would not be able to determine the decision rule adopted. However, this is alleviated by the fact that we explore responses to a sequence of choice tasks for each respondent. We also note that we are not modelling the sequence in which the behavioural rules are implemented by respondents. Case 4 in Eq. (6) does not distinguish whether or a respondent first implemented a EBA-like behavioural heuristic and followed it by a SBA-like rule (or vice versa) nor does it prioritise one rule over another. While interesting, this is not needed for the purposes of this study as we are primarily interested in their implications.

Similarly, in order to investigate EBA-like behaviour setting $\psi_r = 0$—meaning that respondents do not select exclusively among alternatives where attribute level l_k^{SBA} is present—means that the expression is reduced to:

$$\Pr(y_n|\beta,\pi,x_n) = \sum_{q=1}^{Q=2} \pi_q \prod_{t=1}^{T_n} \Pr(i_{nt}|\beta,x_{nit}) \left(1-\psi_q I_{x_{knit}}^{\text{EBA}}\right). \tag{8}$$

If $I_{x_{knit}}^{\text{EBA}}$ is equal to one, the probability of an alternative being chosen among respondents who exhibit EBA-like behaviour (i.e., $\Pr(i_{nt}|\beta,x_{nit})\left(1-\psi_q I_{x_{knit}}^{\text{EBA}}\right) = 0$ when $\psi_{q=1}$) is zero. In all other cases $\left(1-\psi_q I_{x_{knit}}^{\text{EBA}}\right) = 1$, the probability reverts back to $\Pr(i_{nt}|\beta,x_{nit})$. Since only differences in utility matter, we note that in the case where $I_{x_{kn\forall jt}}^{\text{EBA}} = 1$, the choice probabilities are obtained using the MNL model described in Eq. (3).

2.2. Accounting for preference heterogeneity

While the assumption of homogeneity in marginal utilities across respondents may hold in some cases, for a variety of reasons the values are likely to be heterogeneous across respondents. Consequently, we are also interested in capturing the heterogeneity in respondents' marginal utilities within consideration set classes. For this reason, we treat each of the β parameters as finitely distributed random terms, now denoted by β_s to represent preferences with segment s, as shown in the following:

$$\Pr(y_n|\beta,\pi,x_n) = \sum_{c=1}^{C} \pi_c \prod_{t=1}^{T_n} \left(\Pr(i_{nt}|\beta_s,x_{nit})\left(1-\psi_r I_{x_{knit}}^{\text{SBA}}\right)+\psi_r I_{x_{knit}}^{\text{SBA}}\right)\left(1-\psi_q I_{x_{knit}}^{\text{EBA}}\right), \tag{9}$$

where C now encompasses the number of latent segments on the basis of preferences (i.e., $C = Q\times R\times S$, where Q, R and S denotes the number of classes exhibiting different EBA-like behaviour, SBA-like behaviour and preferences respectively). We highlight that the expression Eq. (9) is fully generalisable. For instance, in the case where $Q = R = S = 1$ the model reflects the standard MNL model in Eq. (3); when $Q = 2$ and $R = S = 1$ it is analogous to the EBA-like model outlined in Eq. (8); when $R = 2$ and $Q = S = 1$ it is the same as the SBA-like model outlined in Eq. (7); in the case where $Q = R = 2$ and $S = 1$ it describes the combined model given in Eq. (4); and with $Q = R = 1$ and $S > 1$ it represents a standard latent class model.

3. Survey design and data

The research reported in this paper is based on data obtained from a DCE survey to elicit the general public's preferences for health service innovations in West Yorkshire, UK. Within the DCE, respondents were presented with innovation scenarios differed in terms of six attributes: (i) target population; (ii) age group; (iii) time to get into practice; (iv) the certainty of their likely effects; (v) potential health benefits; and, (vi) cost to an individual taxpayer. Table 1 presents details on these attributes and attribute levels used in the study.

The attributes and their associated levels listed in Table 1 were identified from literature reviews and policy documents (e.g., NICE), interviews with Bradford Foundation Trust managers and Trust members, and a focus group discussion with people who live in the area. Their selection depends on various factors. Some of these are: (1) different needs for an innovation targeting certain population and age group (Olsen, 1997; Tsuchiya, 1999; NICE, 2008), (2) the need for understanding whether the length of time needed to implement an innovation is an important factor for the public and whether they are willing to trade-off potential health benefits for innovations that are implemented sooner, and (3) understanding whether the strength of the evidence underpinning effectiveness and potential health benefit of an innovation are determinants of innovation diffusion and adoption, as raised by others in the literature (e.g., see Grimshaw et al., 2004; Harris and Mortimer, 2008). All attributes and attribute levels are described as realistic by an NHS management team, as well as the participants of the focus group. We also tested the suitability of the attributes and levels using two pilot studies.

The survey attributes, the number of choice tasks, and survey question framing were further tested using two pilot surveys. Having established and tested the attributes and attribute levels, a Bayesian efficient experimental design minimising the D_{error} was generated (see Scarpa and Rose, 2008, for an overview). The priors for the design were informed from the

Table 1. Attributes and attribute levels

Attribute (codes)	Levels (codes)
Target population (*targetp*)	People with disability ($targetp_{disabled}$) People with cancer ($targetp_{cancer}$) People with mental health problems ($targetp_{mental}$) People with obesity ($targetp_{obese}$) People with asthma ($targetp_{asthma}$) People with drug addictions ($targetp_{drug}$)
Age group (*targeta*)	Young (less than 18) ($targeta_{young}$) Adults (18-65) ($targeta_{adult}$) Elderly (more than 65) ($targeta_{elderly}$)
Time to get into practice (*imptime*)	0-5 months ($imptime_{0-5}$) 6-12 months ($imptime_{6-12}$) More than 12 months ($imptime_{12}$)
Whether it works (*eveff*)	It works and scientific studies confirm this ($eveff_{sci}$) It works but not scientifically proven ($eveff_{nosci}$) Experts say it works elsewhere in the NHS ($eveff_{expert}$)
Potential health benefit/gain (*healthg*)	Best health (100%) ($healthg_{100}$) Good health (75%) ($healthg_{75}$) Moderate health (50%) ($healthg_{50}$)
Cost to you as a taxpayer (£/month) (*cost*)	10, 20, 30, and 40

4.1. Estimation results

As a point of reference our analysis starts with the MNL model, which assumes homogeneity of preferences and is based on the conventional RUM individual behavioural rule. According to the MNL results, presented in Table 2, almost all parameter estimates are statistically significant, and are in line with our expectations.[4] The sign of the cost coefficient is both negative and significant, implying that respondents, *ceteris paribus*, prefer less expensive innovations. The alternative specific constant (ASC), which is effects-coded, is also negative and significant for the 'none' option, indicating that respondents, all else being equal, prefer the implementation of additional health service innovations. In general, respondents prefer options that: (1) are proven scientifically or by expert opinion; (2) have more than a 'moderate' health gain; (3) take less than six months to implement; and, (4) target the young and adults. As for the targeted population of the innovations, respondents clearly prefer innovations aimed at people with 'disability', 'cancer', 'mental health problems', and 'asthma', but distinctly dislike innovations that target people with 'drug addiction' and 'obesity'.

Results from the MNL model signal that, on average, respondents consider that innovations targeting people with 'drug addiction' and 'obesity' should be given significantly less priority compared to other population groups. In fact, when compared to the magnitudes of the coefficients retrieved for all other attributes, the coefficients relating to 'drug addiction' and 'obesity' are significantly lower. While this may reflect strong opposition to public health initiatives aimed at addressing 'drug addiction' and 'obesity' relative to other initiatives, it may in part be downwardly biased by a subset of respondents who systematically eliminated alternatives that included either of these so-called 'unfavourable' population levels. In contrast, the coefficient associated with the 'cancer' level significantly exceeds all other coefficients. Again, while this may be due to strong public support for public health innovations aimed at addressing cancer, it is important to account for the fact that a segment of respondents may have reached their decision based solely on this so-called 'favourable' population level. In order to uncover the different choice behaviours exhibited by respondents, we further our analysis to firstly consider EBA- and SBA-like behaviours. Subsequently, we concurrently account for EBA and SBA behaviours with and without preference heterogeneity. In total, we estimate eight models, as summarised in Table 3. For the sake of brevity, in this discussion we only present the findings from four models: MNL, EBA&SBA(1), LC, and EBA&SBA(2). The results from the intermediate models (i.e., EBA and SBA under preference homogeneity and heterogeneity) can be found in Table A1 in Appendix A.

[4] We note that in all models the levels of the qualitative variables are included with the constraint that $\sum_l^L \beta_l = 0$, which is equivalent to effects-coding. To facilitate interpretation, we report coefficients for all levels and their associated standard errors, obtained using the Delta method. We note, though, that the number of parameters and the information criteria measures reported in Tables 2 and A1 account for these constraints.

Table 2. Estimation results[a]

	MNL		EBA&SBA(1)		LC		EBA&SBA(2)	
	est.	st.err	est.	st.err	est.	st.err	est.	st.err
$\hat{\beta}_{1cost}$	-0.011	0.001**	-0.011	0.001**	-0.009	0.002**	-0.009	0.002**
$\hat{\beta}_{1eveff_{nosci}}$	-0.231	0.025**	-0.226	0.026**	-0.243	0.033**	-0.268	0.034**
$\hat{\beta}_{1eveff_{sci}}$	0.176	0.022**	0.181	0.023**	0.173	0.030**	0.210	0.030**
$\hat{\beta}_{1eveff_{expert}}$	0.055	0.023*	0.045	0.024***	0.070	0.029*	0.059	0.029*
$\hat{\beta}_{1healthg_{50}}$	-0.301	0.025**	-0.310	0.026**	-0.325	0.034**	-0.339	0.035**
$\hat{\beta}_{1healthg_{75}}$	0.090	0.022**	0.091	0.023**	0.104	0.028**	0.106	0.027**
$\hat{\beta}_{1healthg_{100}}$	0.211	0.023**	0.218	0.024**	0.222	0.031**	0.233	0.033**
$\hat{\beta}_{1imptime_{0-5}}$	0.068	0.022**	0.069	0.023**	0.072	0.028**	0.076	0.027**
$\hat{\beta}_{1imptime_{6-12}}$	-0.012	0.023	-0.015	0.023	-0.015	0.028	-0.009	0.027
$\hat{\beta}_{1imptime_{12}}$	-0.056	0.022*	-0.054	0.023*	-0.058	0.028*	-0.066	0.028*
$\hat{\beta}_{1targeta_{young}}$	0.097	0.024**	0.098	0.025**	0.116	0.032**	0.127	0.031**
$\hat{\beta}_{1targeta_{adult}}$	0.157	0.025**	0.163	0.026**	0.129	0.032**	0.123	0.032**
$\hat{\beta}_{1targeta_{elderly}}$	-0.254	0.023**	-0.261	0.024**	-0.245	0.030**	-0.250	0.029**
$\hat{\beta}_{1targetp_{disabled}}$	0.466	0.042**	0.546	0.079**	0.308	0.060**	0.646	0.114**
$\hat{\beta}_{1targetp_{drug}}$	-1.351	0.052**	-1.053	0.085**	-1.199	0.084**	-1.095	0.170**
$\hat{\beta}_{1targetp_{cancer}}$	1.379	0.083**	0.476	0.342	1.301	0.119**	0.049	0.544
$\hat{\beta}_{1targetp_{mental}}$	0.327	0.060**	0.476	0.098**	0.314	0.097**	0.688	0.154**
$\hat{\beta}_{1targetp_{obese}}$	-0.955	0.049**	-0.643	0.083**	-0.862	0.076**	-0.725	0.147**
$\hat{\beta}_{1targetp_{asthma}}$	0.133	0.057*	0.199	0.093**	0.138	0.087	0.437	0.137**
$\hat{\beta}_{1ASC_{hypoth}}$	0.781	0.027**	0.978	0.045**	1.784	0.086**	1.795	0.217**
$\hat{\beta}_{1ASC_{none}}$	-0.781	0.027**	-0.978	0.045**	-1.784	0.086**	-1.795	0.217**
$\hat{\beta}_{2cost}$					-0.018	0.003**	-0.025	0.005**
$\hat{\beta}_{2eveff_{nosci}}$					-0.246	0.049**	-0.207	0.063**
$\hat{\beta}_{2eveff_{sci}}$					0.231	0.043**	0.208	0.059**
$\hat{\beta}_{2eveff_{expert}}$					0.015	0.043	-0.001	0.057
$\hat{\beta}_{2healthg_{50}}$					-0.331	0.048**	-0.385	0.065**
$\hat{\beta}_{2healthg_{75}}$					0.086	0.043*	0.047	0.056
$\hat{\beta}_{2healthg_{100}}$					0.245	0.044**	0.338	0.059**
$\hat{\beta}_{2imptime_{0-5}}$					0.063	0.043	0.094	0.056
$\hat{\beta}_{2imptime_{6-12}}$					-0.016	0.044	-0.077	0.058
$\hat{\beta}_{2imptime_{12}}$					-0.047	0.044	-0.017	0.057
$\hat{\beta}_{2targeta_{young}}$					0.103	0.049*	0.103	0.071
$\hat{\beta}_{2targeta_{adult}}$					0.189	0.049**	0.205	0.065**
$\hat{\beta}_{2targeta_{elderly}}$					-0.291	0.050**	-0.308	0.081**
$\hat{\beta}_{2targetp_{disabled}}$					0.844	0.076**	0.435	0.142**
$\hat{\beta}_{2targetp_{drug}}$					-2.071	0.117**	-1.264	0.210**
$\hat{\beta}_{2targetp_{cancer}}$					1.721	0.130**	1.384	0.454**
$\hat{\beta}_{2targetp_{mental}}$					0.558	0.090**	0.248	0.186

Continued on next page

Table 2: Estimation results[a] (cont'd)

	MNL		EBA&SBA(1)		LC		EBA&SBA(2)	
	est.	st.err	est.	st.err	est.	st.err	est.	st.err
$\hat{\beta}_{2targetp_{obese}}$					-1.326	0.100**	-0.605	0.163**
$\hat{\beta}_{2targetp_{asthma}}$					0.274	0.093**	-0.197	0.191
$\hat{\beta}_{2ASC_{hypoth}}$					0.236	0.046**	0.439	0.084**
$\hat{\beta}_{2ASC_{none}}$					-0.236	0.046**	-0.439	0.084**
$\pi_{1,\mathrm{RUM}}$	1.000	fixed	0.406	0.102**	0.609	0.024**	0.203	0.074**
$\pi_{1,\mathrm{EBA}}$			0.041	0.020*			0.040	0.020*
$\pi_{1,\mathrm{SBA}}$			0.421	0.102**			0.392	0.068**
$\pi_{1,\mathrm{EBA\&SBA}}$			0.131	0.023**			0.137	0.023**
$\pi_{2,\mathrm{RUM}}$					0.391	0.024**	0.214	0.088*
$\pi_{2,\mathrm{EBA}}$							0.000	0.000
$\pi_{2,\mathrm{SBA}}$							0.015	0.083
$\pi_{2,\mathrm{EBA\&SBA}}$							0.000	0.000
$LL(\hat{\beta})$	-6,390.409		-5,668.292		-5,854.472		-5,349.261	
K	15		18		31		37	
$\bar{\rho}^2$	0.182		0.274		0.248		0.312	
AIC	12,811.154		11,372.724		11,770.943		10,772.523	
BIC	12,913.798		11,496.038		11,983.969		11,026.779	
$CAIC$	12,928.766		11,514.571		12,014.969		11,063.779	

[a]Due to rounding, some of the coefficients and standard errors appear to be zero.

*Parameter is significantly different from zero at the 5% level.

**Parameter is significantly different from zero at the 1% level.

Table 3. Model specifications

Model	EBA-like behaviour	SBA-like behaviour	Preference heterogeneity
MNL	✗	✗	✗
EBA(1)	✓	✗	✗
SBA(1)	✗	✓	✗
EBA&SBA(1)	✓	✓	✗
LC	✗	✗	✓
EBA(2)	✓	✗	✓
SBA(2)	✗	✓	✓
EBA&SBA(2)	✓	✓	✓

Referring back to Table 2, Model EBA&SBA(1) accommodates situations in which respondents adopt one or more of the individual behavioural rules. Accommodating for all four individual behavioural rules concurrently appears to be much better suited to explaining respondents' choices. Indeed, it is obvious that a move from MNL to EBA&SBA(1) leads to a dramatic improvement in model fit (by over 722 log-likelihood units at the expense of just three additional parameter). The fact that the proportion predicted to exhibit each behavioural rule is non-trivial, also raises some concerns about the appropriateness of assuming the deterministic choice set and the importance of accounting for all possible rules simultaneously.

The findings from the MNL also holds in EBA&SBA(1): respondents prefer innovations that are scientifically proven or confirmed by expert opinion, have more than 'moderate' health benefits, take less than six months to implement, target the young and adults and cost less. While the results also imply that respondents prefer innovations targeting people with 'disability', 'cancer', 'mental health problems', and 'asthma', but dislike innovations that target people with 'drug addiction' and 'obesity'. The coefficients pertaining to the 'drug addiction', 'obesity', and 'cancer' levels appear to be relatively less extreme. On this basis, the coefficient retrieved for these levels under the MNL model would appear to be considerably biased. This reinforces the necessity of accounting for EBA- and SBA-like behaviours concurrently.

According to the results, approximately, 59 percent of the respondent used EBA- and/or SBA-like behaviours, and only 41 percent of the respondents based their choices on conventional RUM. Among the respondents, over 17 percent exhibited EBA-like behaviour, approximately 55 percent used a SBA-like strategy, and 13 percent exhibited both EBA- and SBA-like behaviours. This finding clearly shows that for this empirical dataset, at least, the conventional RUM assumption may hold only for a minority of respondents. Instead, the idea that respondents systematically derive their individual behavioural rules on the basis of the attribute-levels presented in the choice task cannot be ruled out. [5]

Because it might be unrealistic to assume homogeneity of preferences, and the potential risk of confounding between preference heterogeneity and choice behaviour (see Hess et al., 2013, for a discussion on this issue), we estimate additional models. These are based on the same individual behavioural rules, but where we assume that there are two latent classes of preferences.[6]

From the results of the LC model, it appears that respondents can be segmented according to their different preferences: one accounting for 61 percent of respondents and another accounting for 39 percent of respondents. In both segments the implied ranking of preferences are comparable and are broadly in line with those already discussed. The main difference between the two segments appears to be that the first segment is relatively less price sensitive compared to the second segment. Comparing the model fit attained under LC model to that obtained its preference homogeneity counterpart (MNL), we demonstrate the importance of accounting for preference heterogeneity (over 530 log-likelihood units

[5]These findings are clearly illustrated in the mosaic plot in Figure A1 in Appendix A.

[6]Given our focus on accommodating a range of choice behaviours, rather than fully uncovering all latent segments of preferences, we limited our analysis to only two latent classes of preferences. We also recognise that we have assumed a finite representation of the unobserved taste variation. While our motivation for this was partly driven by our desire to straightforwardly compare the processing strategies across different latent classes of preferences, the approach could easily be implemented within a random parameter context or even using the combined latent class random parameters logit model (e.g., see Hess et al., 2013; Campbell et al., 2014, for further details and empirical examples). We suggest that these represent interesting extensions to our approach.

improvement). Importantly, looking at the $\bar{\rho}^2$ and information criteria indicates that this improvement is supported, even after accounting for the large number of additional parameters. However, we find that when the LC model fit is compared against those that account for EBA- and SBA-like behaviours under preference homogeneity, the model fit achieved under LC model is substantially lower. Given the recent emphasis and elevation of a host of models to account for preference heterogeneity within the literature,this is a significant finding. Findings from this empirical dataset, at least, would suggest that, while not in vain, potentially more rewarding results may have been attained had more focus been diverted to looking at processing strategies, such as EBA- and SBA-like behaviours rather than solely addressing unobserved preference heterogeneity.

Turning our attention to the final model presented in Table 2, EBA&SBA(2) which is similar to EBA&SBA(1) in that it accommodates all four individual behavioural rules concurrently, but that it also takes preference heterogeneity into account, we find evidence of heterogeneous preferences towards health service innovations. The majority of the sample (almost 80 percent) can be identified as belonging to the first segment of respondents' preferences. Focusing on the behavioural rules adopted by respondents within these preference segments, we find that just over one-quarter of them based their choices on the RUM rule. In total, almost 70 percent of respondents within this first preference segment exhibited only SBA-like behaviour, while around 23 percent used an EBA-like processing strategy. Investigating the individual behavioural rules adopted by respondents in the second segment of preferences reveals that, almost all of them (93 percent) used the conventional RUM rule.[7] In terms of model fit, we observe an improvement of over 500 log-likelihood units compared to its preference homogeneity counterpart (EBA&SBA(1)). This suggests that our elaborate model can be considered as the model that best explains respondents' individual behavioural rules and preferences.

Overall, we observe that when preference heterogeneity is accommodated large improvements in model fits are obtained. But what is even more interesting are the stark differences in the processing strategies adopted within each preference segment. We generally find that the decision rules are much more prevalent within the largest segment. In fact, there is even evidence to suggest that within the smaller segment that only a minority of them used a processing strategy.

4.2. Marginal willingness-to-pay estimates

Any meaningful comparison of preference heterogeneity across the various models is not possible, since each model is subject to a different scaling. What does make comparative sense are the implied marginal WTP estimates, since the scale effect is neutralised. In Table 4,

[7]The different individual rules adopted by each segment of preferences is especially apparent in Figure A1 presented in Appendix A.

Table 4. Marginal willingness to pay estimates (£ per month)[a]

	MNL	EBA&SBA(1)	LC [b]	EBA&SBA(2) [b]
$\hat{WTP}_{eveff_{nosci}}$	-36.31	-35.93	-38.31	-44.76
	(-47.87,-24.75)	(-47.83,-24.04)	(-51.66,-24.97)	(-67.92,-21.60)
$\hat{WTP}_{eveff_{expert}}$	-10.72	-12.03	-11.58	-14.86
	(-17.73,-3.72)	(-19.47,-4.59)	(-18.85,-4.32)	(-26.49,-3.24)
$\hat{WTP}_{healthg_{75}}$	34.91	35.39	37.84	42.12
	(23.60,46.21)	(23.77,47.02)	(24.34,51.34)	(20.72,63.51)
$\hat{WTP}_{healthg_{100}}$	45.77	46.6	49.22	55.62
	(32.65,58.88)	(32.85,60.34)	(33.27,65.16)	(29.84,81.39)
$\hat{WTP}_{imptime_{6-12}}$	-7.12	-7.44	-7.54	-8.82
	(-14.02,-0.21)	(-14.62,-0.26)	(-14.72,-0.36)	(-19.13,1.48)
$\hat{WTP}_{imptime_{12}}$	-11.11	-10.91	-11.12	-13.17
	(-18.30,-3.93)	(-18.24,-3.58)	(-18.66,-3.59)	(-24.32,-2.03)
$\hat{WTP}_{targeta_{young}}$	31.33	31.66	32.81	36.05
	(21.09,41.56)	(21.09,42.23)	(20.97,44.65)	(17.48,54.61)
$\hat{WTP}_{targeta_{adult}}$	36.71	37.34	35.6	36.63
	(24.52,48.90)	(24.73,49.95)	(22.14,49.07)	(16.46,56.80)
$\hat{WTP}_{targetp_{disabled}}$	12.39	6.15	5.87	-1.90
	(-2.32,27.10)	(-9.50,21.80)	(-10.73,22.47)	(-27.48,23.68)
$\hat{WTP}_{targetp_{drug}}$	-149.77	-134.85	-159.03	-166.67
	(-186.08,-113.45)	(-169.01,-100.68)	(-199.05,-119.01)	(-241.06,-92.27)
$\hat{WTP}_{targetp_{cancer}}$	93.96	-0.00	91.53	-44.30
	(64.66,123.27)	(-72.36,72.36)	(56.66,126.40)	(-184.10,95.51)
$\hat{WTP}_{targetp_{obese}}$	-114.46	-98.69	-120.08	-128.84
	(-143.74,-85.17)	(-126.18,-71.21)	(-152.67,-87.49)	(-191.50,-66.18)
$\hat{WTP}_{targetp_{asthma}}$	-17.31	-24.41	-18.05	-25.65
	(-32.57,-2.05)	(-40.93,-7.89)	(-35.95,-0.14)	(-51.89,0.58)

[a]Values in parenthesis represent 95% confidence intervals, obtained using the Delta method.

[b]For ease of comparison, the marginal WTP estimates have been weighted according to the unconditional class membership probabilities.

we compare the marginal WTP estimates (against a baseline attribute level) derived from the models presented in Table 2.[8]

Of central relevance is whether or not there is any general change in the marginal WTP estimates as one moves from the standard MNL model to the model that accounts for a range of processing strategies and preference heterogeneity, EBA&SBA(2). We remark that the WTP estimates for the attributes, except from 'target population', largely remain unchanged across the models. With respect to these attribute levels, as already deduced from the results in Table 2, irrespective of the model specification, respondents are willing to pay most for innovations that are scientifically proven (around £40 more per month compared to unscientifically

[8]The marginal utilities for SBA and EBA models under both preference homogeneity and heterogeneity can be found in Table A2.

proven innovations), have at least above a moderate health benefit (approximately £35 more per month relative to a moderate health benefit), take less than six months to implement (in the region of £12 per month compared to innovations that require 12 months), and target adults and the young (both in the ball park of £35 more per month compared to those targeting the elderly).

All else being equal, compared to the 'mental health problem' target population level, the results show that respondents dislike spending on innovations targeting people with 'drug addiction', 'obesity', and 'asthma' and are willing to pay more for those targeting 'cancer patients' and 'disabled' people. This generally holds across all models. Nonetheless, there are a number of notable differences in the estimated values of marginal WTP associated with the 'target population' attribute as one progresses from the standard MNL to our most elaborate model, EBA&SBA(2).

In the case of the 'elimination' decision rule with respect to the 'drug addiction' and 'obesity' levels, we see that not accounting for this type of behaviour resulted in inflated average marginal WTP values. This holds true in both the models accounting for homogeneous (MNL vis-à-vis EBA&SBA(1)) and heterogeneous (LC vis-à-vis EBA&SBA(2)) preferences. This is not surprising given the fact that the marginal WTP estimates obtained from the models that account for this EBA-like behaviour effectively only applies to the subset who did not adopt this processing strategy.[9] This led to the slight increase in marginal WTP.

Conversely, in the case of the 'selection' decision rule, in which alternatives are selected with respect to whether innovations are aimed at cancer patients, we observe a decrease in the estimated average marginal WTP estimates, under both homogeneous (MNL vis-à-vis EBA&SBA(1)) and heterogeneous (LC vis-à-vis EBA&SBA(2)) specifications. Again, this reflects the fact that the coefficients uncovered from the SBA-like models are actually based on the choices made by respondents who did not use this decision-making strategy.[10] Therefore, the reported marginal WTP estimates retrieved from the models accommodating the 'selection' decision rule effectively only applies to the subset who did not employ this strategy.

Notwithstanding the notable differences in the marginal WTP estimates obtained from all models, in particular for innovations targeting people with 'cancer', 'drug addiction' and 'obesity', there is only partial statistical evidence to confirm these differences. In particular, we find statistical evidence that the innovations targeting 'cancer' patients do vary across our models.

[9] Respondents who used the EBA-like decision rule did not make any trade-offs between either the 'drug addiction' or 'obesity' attribute levels and the other attributes. The retrieved coefficients associated with these levels in the models accommodating EBA-like behaviour, therefore, reflects the preferences of the remaining respondents.

[10] As in the case of the EBA-like behaviour, respondents who adopted a SBA-like decision rule did not make any trade-offs between the 'cancer patients' level and the other attributes. For this reason, the coefficients for the 'cancer patients' level in the case of the SBA-like models reflects the preferences of the subgroup of respondents who did not exhibit this type of behaviour.

4.3. Scenario analysis for choice probabilities of policy options

To further tease out the effects of decision rules, we explore choice probabilities for different policy options in this scenario analysis. This analysis uses the parameter estimates reported in Tables 2 to assess choice predictions under each of the model specifications discussed earlier. For this analysis, we compare a 'no investment' policy option against a policy option that has the following features: (1) entails an increase in monthly tax contributions of £40, (2) is scientifically proven, (3) results in a maximum health gain, (4) takes less than six months to implement, and (5) targets young people. Given our interest on the 'target population' attribute, we take each of its levels in turn to uncover the choice predictions. Results from this analysis are presented in Table 5.[11]

The choice predictions show some similarities and variations under the four model specifications. In particular, the choice predictions, all else being equal, for innovations targeting people with disability, mental health, and asthma are relatively consistent across all specifications. In all three cases, our analysis reveals that irrespective of the model assumptions approximately 90 percent of respondents would prefer the hypothetical innovations to be implemented over the 'no investment' options. However, and not surprising, given the high incidence of EBA- and SBA-like behaviours identified in this sample, we do observe more salient differences across the models in the predicted choice probabilities relating to the innovations aimed at tackling drug addiction, obesity and cancer.

Focusing firstly on the differences between predictions associated with the levels linked with EBA-like behaviour, we find that the shares of respondents who are predicted to choose the policy scenarios which include 'drug addiction', and 'obesity' are relatively stable across models assuming homogeneous preferences (MNL and EBA&SBA(1)), around 60 percent and 67 percent in the case of 'drug addiction', and 'obesity'. However, when we turn our attention to the choice predictions retrieved from the models assuming heterogeneous preferences (LC and EBA&SBA(2)) we find more obvious differences. Specifically, in the case of scenario involving 'drug users' we find that the share drops from around 63 percent to approximately 45 percent as we move from LC to EBA&SBA(2). This drop is even more striking in the case of innovations targeting people with 'obesity'. The respective fall is from almost 70 percent to around 46 percent. The fact that these drops are statistically significant for both attribute levels is important. It suggests that, while marginal WTP estimates did not vary significantly, the level of public support and acceptance of the innovations is sensitive to whether or not EBA-like behaviour is addressed.

Moving to the levels connected with SBA-like decision rules are accounted for, we again only see minor differences in the choice predictions obtained under MNL and EBA&SBA(1) for the innovation targeting 'cancer'. Nevertheless, when random taste variation is accommodated we

[11] For comparison of choice predictions under our other models addressing EBA- or SBA-like behaviours, refer to Table A3 in Appendix A.

Table 5. Choice predictions[a]

	$targetp_{disabled}$	$targetp_{drug}$	$targetp_{cancer}$	$targetp_{mental}$	$targetp_{obese}$	$targetp_{asthma}$
MNL	0.894	0.578	0.955	0.880	0.671	0.858
	(0.880,0.908)	(0.544,0.613)	(0.945,0.964)	(0.861,0.899)	(0.640,0.701)	(0.834,0.882)
EBA&SBA(1)	0.932	0.607	0.967	0.927	0.667	0.906
	(0.921,0.943)	(0.573,0.641)	(0.956,0.978)	(0.913,0.942)	(0.635,0.699)	(0.888,0.925)
LC[b]	0.903	0.628	0.954	0.882	0.689	0.856
	(0.884,0.921)	(0.593,0.664)	(0.941,0.968)	(0.858,0.905)	(0.655,0.723)	(0.827,0.886)
EBA&SBA(2)[b]	0.933	0.450	0.770	0.925	0.466	0.900
	(0.892,0.974)	(0.348,0.552)	(0.615,0.924)	(0.878,0.972)	(0.362,0.571)	(0.837,0.962)

[a]Values in parenthesis represent 95% confidence intervals, obtained using the Delta method.

[b]For ease of comparison, the choice prediction estimates have been weighted according to the unconditional class membership probabilities.

do see quite a large (and significant) reduction in the proportion predicted under EBA&SBA(2) (approximately 78 percent) compared to the share suggest under LC (around 96 percent). This, again, signals the consequences of the upwardly biased preference coefficient(s) for 'cancer' when SBA-like behaviour is not accommodated. Ultimately, policy decisions based on models which do not recognise nor account for this are likely to result in erroneous and inappropriate policy decisions.

5. Conclusions

This paper proposes a flexible method for exploring choice behaviours in which respondents within a stated choice context make decisions based on certain elimination and/or selection criteria, whilst addressing preference heterogeneity. In addition to the conventional random utility maximisation (RUM), the method examines the incidence of two types of decision-making heuristics: (i) behaviour resembling elimination-by-aspects (EBA); and, (ii) behaviour resembling selection-by-aspects (SBA) in the context of a discrete choice experiment (DCE) exploring the public's preferences for health service innovation implementation prioritisation. Specifically, we set out to reveal the extent to which the choices made by respondents during the DCE were based on EBA- and SBA-like behaviours that stemmed from the population at which the innovation was aimed. In so doing we were able to determine whether or not a subset of respondents systematically restricted their actual choice set to only include alternatives that ensured certain population groups would be targeted.

The paper presents an intuitive approach to explore these issues. Its appeal stems from the fact that it provides a probabilistic estimate of the proportion of the sample who adopted a range of different individual behavioural rules. We began our analysis under the assumption that all respondents adopted the conventional RUM decision rule, then, in turn, allowed for EBA-like behaviour, SBA-like behaviour, and finally permitted a combination of all three individual behavioural rules. Following this, we replicated the analysis, but accommodated random taste variation.

Our findings show that accommodating EBA- and SBA-like choice behaviours concurrently prove to give a richer insight into respondents' behaviour and suggest that as few as 40 percent of the sample adopt the conventional RUM decision rule. In line with previous studies, we find that assuming homogeneous preferences in respondents is inappropriate. Going beyond this, we also show that each segment of respondents differs in their preferences, but they also adopt different decision-making heuristics.

Crucially, the results show that failing to account for EBA- and/or SBA-like choice behaviours is not optimal. Where our models account for such behaviours they outperform those based solely on the random utility maximisation assumption. Whilst recognising that we assume a finite representation of the unobserved taste variation, just accounting for the EBA- and SBA-like behaviours concurrently leads to a substantially improved fit (by almost 200 log-likelihood units) compared to simply addressing preference heterogeneity. Given the predominant emphasis of accounting for preference heterogeneity within the discrete choice literature in recent years and the elevation of a host of models to account for it, this is a significant finding. This would suggest that, while not in vain, potentially more rewarding results may have been attained have more focus been diverted to looking at processing strategies, such as EBA and SBA, rather than preference heterogeneity. It is, off course, acknowledged that this finding may not be generalisable to other datasets, but we feel that it does shed additional light on the manner in which respondents reach their final decision and could help lead to more reliable models. We encourage others to implement the approach in their own datasets so that the generalisability of these findings can be judged.

As would be expected, failing to account for the EBA- and SBA-like behaviours leads to biased marginal WTP estimates. The exploration of choice predictions for a range of scenarios also reveals that naïvely assuming that respondents adopt the conventional random utility maximisation rule is misguided.

Although this paper highlights the importance of and need for accommodating EBA- and SBA-like decision rules, there are some limitations which are left for future research. Firstly, while we wanted to bring the issue of EBA- and SBA-like behaviours to the fore, we appreciate that there are a number of other decision-making heuristics and processing strategies that we did not address in this paper. This would be particularly important if one aims to explore meaningful differences among heuristics. Secondly, while our latent class segmentation of preferences affords a readily identification of heterogeneity, we recognise that it would have been possible to further uncover within class continuous taste variation. However, this would entail considerably more computational effort. Finally, the welfare estimates derived in this study are based on a small subset of respondents (c. 42 percent) who did not adopt a decision rule. Therefore, interpretation of the welfare estimates requires caution.

To conclude, we feel that this work demonstrates that further exploration in this area is justified. Nevertheless, the models illustrated here provide additional insight into the manner in which respondents arrive at their final decision. This represents an exciting research challenge.

Appendix A. Accounting for EBA- and SBA-like behaviours separately

Table A1. Estimation results for EBA and SBA models[a]

	EBA(1)		SBA(1)		EBA(2)		SBA(2)	
	est.	st.err	est.	st.err	est.	st.err	est.	st.err
$\hat{\beta}_{1cost}$	-0.012	0.001**	-0.011	0.001**	-0.009	0.002**	-0.009	0.002**
$\hat{\beta}_{1eveff_{nosci}}$	-0.225	0.026**	-0.230	0.025**	-0.260	0.033**	-0.246	0.033**
$\hat{\beta}_{1eveff_{sci}}$	0.175	0.023**	0.184	0.023**	0.195	0.029**	0.181	0.031**
$\hat{\beta}_{1eveff_{expert}}$	0.050	0.023*	0.046	0.023*	0.065	0.028*	0.066	0.030*
$\hat{\beta}_{1healthg_{50}}$	-0.309	0.026**	-0.302	0.025**	-0.330	0.035**	-0.330	0.035**
$\hat{\beta}_{1healthg_{75}}$	0.093	0.023**	0.088	0.022**	0.109	0.027**	0.102	0.028**
$\hat{\beta}_{1healthg_{100}}$	0.216	0.024**	0.213	0.024**	0.220	0.032**	0.227	0.032**
$\hat{\beta}_{1imptime_{0-5}}$	0.066	0.023**	0.074	0.023**	0.069	0.027**	0.078	0.029**
$\hat{\beta}_{1imptime_{6-12}}$	-0.009	0.022	-0.020	0.023	0.002	0.029	-0.022	0.029
$\hat{\beta}_{1imptime_{12}}$	-0.056	0.023*	-0.054	0.023*	-0.071	0.027**	-0.056	0.028*
$\hat{\beta}_{1targeta_{young}}$	0.095	0.025**	0.099	0.024**	0.119	0.031**	0.120	0.032**
$\hat{\beta}_{1targeta_{adult}}$	0.163	0.026**	0.159	0.025**	0.127	0.031**	0.129	0.033**
$\hat{\beta}_{1targeta_{elderly}}$	-0.258	0.024**	-0.258	0.024**	-0.246	0.029**	-0.248	0.030**
$\hat{\beta}_{1targetp_{disabled}}$	0.375	0.045**	0.712	0.064**	0.379	0.066**	0.522	0.114**
$\hat{\beta}_{1targetp_{drug}}$	-1.218	0.058**	-1.105	0.071**	-1.329	0.119**	-0.991	0.126**
$\hat{\beta}_{1targetp_{cancer}}$	1.343	0.089**	0.117	0.266	1.398	0.121**	0.207	0.518
$\hat{\beta}_{1targetp_{mental}}$	0.289	0.067**	0.592	0.081**	0.368	0.106**	0.548	0.147**
$\hat{\beta}_{1targetp_{obese}}$	-0.805	0.054**	-0.710	0.069**	-0.954	0.091**	-0.657	0.124**
$\hat{\beta}_{1targetp_{asthma}}$	0.016	0.062	0.395	0.078**	0.138	0.091	0.371	0.139**
$\hat{\beta}_{1ASC_{hypoth}}$	1.066	0.031**	0.654	0.037**	1.948	0.209**	1.670	0.097**
$\hat{\beta}_{1ASC_{none}}$	-1.066	0.031**	-0.654	0.037**	-1.948	0.209**	-1.670	0.097**
$\hat{\beta}_{2cost}$					-0.024	0.004**	-0.017	0.003**
$\hat{\beta}_{2eveff_{nosci}}$					-0.208	0.062**	-0.242	0.050**
$\hat{\beta}_{2eveff_{sci}}$					0.209	0.058**	0.242	0.044**
$\hat{\beta}_{2eveff_{expert}}$					-0.001	0.100	-0.001	0.100
$\hat{\beta}_{2healthg_{50}}$					-0.388	0.064**	-0.330	0.049**
$\hat{\beta}_{2healthg_{75}}$					0.051	0.055	0.085	0.044
$\hat{\beta}_{2healthg_{100}}$					0.337	0.057**	0.245	0.046**
$\hat{\beta}_{2imptime_{0-5}}$					0.094	0.055	0.070	0.044
$\hat{\beta}_{2imptime_{6-12}}$					-0.078	0.057	-0.028	0.044
$\hat{\beta}_{2imptime_{12}}$					-0.016	0.055	-0.042	0.046
$\hat{\beta}_{2targeta_{young}}$					0.097	0.069	0.107	0.049*
$\hat{\beta}_{2targeta_{adult}}$					0.204	0.064**	0.192	0.049**
$\hat{\beta}_{2targeta_{elderly}}$					-0.301	0.077**	-0.299	0.051**
$\hat{\beta}_{2targetp_{disabled}}$					0.426	0.108**	1.087	0.098**

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Table A1. Estimation results for EBA and SBA models[a] (cont'd)

	EBA(1)		SBA(1)		EBA(2)		SBA(2)	
	est.	st.err	est.	st.err	est.	st.err	est.	st.err
$\hat{\beta}_{2targetp_{drug}}$					-1.290	0.180**	-1.836	0.130**
$\hat{\beta}_{2targetp_{cancer}}$					1.445	0.165**	0.480	0.338
$\hat{\beta}_{2targetp_{mental}}$					0.247	0.145	0.821	0.114**
$\hat{\beta}_{2targetp_{obese}}$					-0.633	0.130**	-1.084	0.118**
$\hat{\beta}_{2targetp_{asthma}}$					-0.195	0.154	0.531	0.114**
$\hat{\beta}_{2ASC_{hypoth}}$					0.452	0.070**	0.106	0.058*
$\hat{\beta}_{2ASC_{none}}$					-0.452	0.070**	-0.106	0.058*
$\pi_{1,\mathrm{RUM}}$	0.827	0.016**	0.363	0.057**	0.590	0.045**	0.242	0.086**
$\pi_{1,\mathrm{EBA}}$	0.173	0.016**			0.177	0.016**		
$\pi_{1,\mathrm{SBA}}$			0.637	0.057**			0.367	0.086**
$\pi_{1,\mathrm{EBA\&SBA}}$								
$\pi_{2,\mathrm{RUM}}$					0.234	0.045**	0.152	0.031**
$\pi_{2,\mathrm{EBA}}$					0.000	0.000		
$\pi_{2,\mathrm{SBA}}$							0.239	0.032**
$\pi_{2,\mathrm{EBA\&SBA}}$								
$LL(\hat{\beta})$	-5,672.681		-6,381.366		-5,352.373		-5,846.307	
K	16		16		33		33	
$\bar{\rho}^2$	0.274		0.183		0.312		0.249	
AIC	11,377.714		12,794.760		10,770.746		11,758.613	
BIC	11,487.485		12,904.531		10,997.515		11,985.382	
$CAIC$	11,503.166		12,920.926		11,030.515		12,018.382	

[a]Due to rounding, some of the coefficients and standard errors appear to be zero.

*Parameter is significantly different from zero at the 5% level.

**Parameter is significantly different from zero at the 1% level.

Table A2. Marginal willingness to pay estimates for EBA and SBA models (£ per month)[a]

	EBA(1)	SBA(1)	EBA(2)	SBA(2)
$\hat{WTP}_{eveff_{nosci}}$	-34.51 (-45.65,-23.37)	-38.03 (-50.62,-25.44)	-41.35 (-57.24,-25.47)	-40.24 (-51.86,-28.62)
$\hat{WTP}_{eveff_{expert}}$	-10.77 (-17.69,-3.86)	-12.63 (-20.36,-4.89)	-12.61 (-20.78,-4.45)	-13.4 (-20.61,-6.20)
$\hat{WTP}_{healthg_{75}}$	34.71 (23.56,45.85)	35.8 (23.82,47.79)	40.26 (24.90,55.62)	38.99 (27.69,50.30)
$\hat{WTP}_{healthg_{100}}$	45.28 (32.38,58.17)	47.31 (33.05,61.57)	52.15 (34.15,70.15)	51.22 (37.77,64.67)
$\hat{WTP}_{imptime_{6-12}}$	-6.47 (-13.25,0.31)	-8.65 (-16.13,-1.17)	-7.14 (-14.80,0.52)	-9.03 (-15.94,-2.12)
$\hat{WTP}_{imptime_{12}}$	-10.52 (-17.57,-3.47)	-11.76 (-19.37,-4.16)	-12.51 (-20.92,-4.10)	-11.69 (-18.70,-4.68)
$\hat{WTP}_{targeta_{young}}$	30.49 (20.51,40.47)	32.83 (21.78,43.88)	33.86 (20.89,46.83)	34.39 (24.11,44.68)
$\hat{WTP}_{targeta_{adult}}$	36.36 (24.30,48.42)	38.28 (25.27,51.30)	35.52 (20.73,50.30)	36.94 (25.39,48.49)
$\hat{WTP}_{targetp_{disabled}}$	7.47 (-7.70,22.63)	11.07 (-4.16,26.29)	2.55 (-16.74,21.85)	4.21 (-9.51,17.92)
$\hat{WTP}_{targetp_{drug}}$	-130.08 (-161.58,-98.58)	-155.87 (-195.94,-115.80)	-154.27 (-204.02,-104.51)	-165.7 (-204.19,-127.20)
$\hat{WTP}_{targetp_{cancer}}$	91 (61.19,120.81)	-43.61 (-103.45,16.24)	96.09 (54.09,138.09)	-31.14 (-92.37,30.09)
$\hat{WTP}_{targetp_{obese}}$	-94.43 (-119.54,-69.33)	-119.59 (-152.14,-87.05)	-117.16 (-158.16,-76.16)	-125.76 (-156.03,-95.49)
$\hat{WTP}_{targetp_{asthma}}$	-23.52 (-39.43,-7.61)	-18.06 (-34.02,-2.10)	-23.18 (-43.11,-3.24)	-18.73 (-33.15,-4.31)

[a]Values in parenthesis represent 95% confidence intervals, obtained using the Delta method.

[b]For ease of comparison, the marginal WTP estimates have been weighted according to the unconditional class membership probabilities.

Table A3. Choice predictions for EBA and SBA models[a]

	$targetp_{disabled}$	$targetp_{drug}$	$targetp_{cancer}$	$targetp_{mental}$	$targetp_{obese}$	$targetp_{asthma}$
EBA(1)	0.931 (0.920,0.941)	0.605 (0.571,0.639)	0.972 (0.966,0.979)	0.925 (0.911,0.939)	0.665 (0.634,0.697)	0.903 (0.885,0.922)
SBA(1)	0.896 (0.882,0.911)	0.584 (0.548,0.619)	0.937 (0.918,0.956)	0.884 (0.865,0.904)	0.675 (0.645,0.706)	0.863 (0.839,0.886)
EBA(2)[b]	0.933 (0.916,0.950)	0.445 (0.369,0.521)	0.972 (0.961,0.982)	0.925 (0.904,0.945)	0.461 (0.384,0.539)	0.899 (0.874,0.925)
SBA(2)[b]	0.905 (0.874,0.936)	0.631 (0.559,0.702)	0.790 (0.684,0.895)	0.886 (0.846,0.926)	0.692 (0.627,0.757)	0.861 (0.811,0.910)

[a]Values in parenthesis represent 95% confidence intervals, obtained using the Delta method.

[b]For ease of comparison, the choice prediction estimates have been weighted according to the unconditional class membership probabilities.

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