A036 Elimination and selection by aspects in health choice experiments: Prioritising health service innovations

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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 behaviour, 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.

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

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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. Despite the appeal of methods such as cost-effectiveness, 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.

Notwithstanding the appeal of DCEs, and its use in various fields, including health economics, 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; Campbell et al., 2011; 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). 'Elimination-by-aspects' (EBA) and 'selection-by-aspects' (SBA) are examples of such processing strategies that consist of respondents eliminating or selecting some alternatives based on some decision criteria. There are various factors that might be contributing 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; 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, EBA and SBA behaviour has largely been overlooked. This paper furthers this line of enquiry and explores EBA and SBA behaviour 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 behaviour 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-like and SBA-like choice behaviour, 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-like 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 and welfare analysis.

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-like and SBA-like behaviour 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:

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

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 rationally restrict their consideration set to include only those alternatives that meet a specific condition, this assumption may not necessarily be appropriate. 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-like 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. Accommodating EBA-like choice behaviour

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. To account for this type of behaviour the choice probability in Eq. 3 can be written as:

$$\Pr\left(y_n|\beta, \pi, x_n\right) = \sum_{q=1}^{Q=2} \pi_q \prod_{t=1}^{T_n} \Pr\left(i_{nt}|\beta, x_{nit}\right)\left(1 - \psi_q I^{\text{EBA}}_{x_{knit}}\right), \tag{4a}$$

where $I^{\text{EBA}}_{x_{knit}}$ is an indicator variable denoting whether the level of attribute k, l^{EBA}_k, that is taken as 'criterion' for elimination of alternatives, is present in alternative i in choice occasion t faced by respondent n:

$$I^{\text{EBA}}_{x_{knit}} = \begin{cases} 1 & \text{if } x_{knit} = l^{\text{EBA}}_k; \\ 0 & \text{otherwise.} \end{cases} \tag{4b}$$

ψ_r is a discrete variable, taking the values of 1 or 0, denoting whether or not the respondent eliminated the attribute level l^{EBA}_k from their choice set:

$$\psi_q = \begin{cases} 1 & \text{if } l^{\text{EBA}}_k \text{ is eliminated from the choice task;} \\ 0 & \text{otherwise.} \end{cases} \tag{4c}$$

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

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_q. Therefore, $\pi_{q=1}$, which is associated with $\psi_{q=1}$, represents the (unconditional) probability that respondents eliminated alternatives containing attribute level l^{EBA}_k from their choice sets. In contrast, $\psi_{q=0}$, which is associated with $\psi_{q=0}$, denotes the (unconditional) probability that respondents do not show such processing strategy (in other words, the behaviour reflects RUM). We then estimate these probabilities, along with the attribute parameters using maximum likelihood estimation procedure.

2.2. Accommodating SBA-like choice behaviour

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. The choice probability can now be written as:

$$\Pr\left(y_n|\beta,\pi,x_n\right) = \sum_{r=1}^{R=2} \pi_r \prod_{t=1}^{T_n} \Pr\left(i_{nt}|\beta, x_{nit}\right)\left(1-\psi_r I^{\text{SBA}}_{x_{knit}}\right) + \psi_r I^{\text{SBA}}_{x_{knit}}, \tag{5a}$$

where $I^{\text{SBA}}_{x_{knit}}$ is an indicator variable denoting whether the level of an attribute k, l^{SBA}_k, that respondents use as 'decision criteria' for the selection of alternatives, is present in alternative i in choice occasion t faced by respondent n:

$$I^{\text{SBA}}_{x_{knit}} = \begin{cases} 1 & \text{if } x_{knit} = l^{\text{SBA}}_k; \\ 0 & \text{otherwise.} \end{cases} \tag{5b}$$

ψ_q is a discrete variable with possible values of 1 or 0, representing whether or not the respondents exhibited SBA-like behaviour:

$$\psi_r = \begin{cases} 1 & \text{if } l^{\text{SBA}}_k \text{ is selected from the choice task;} \\ 0 & \text{otherwise.} \end{cases} \tag{5c}$$

Under this framework, the probability of an alternative being chosen in cases where $I^{\text{SBA}}_{x_{knit}} = 1$ is one among respondents who exhibit SBA-like behaviour (i.e., $\Pr\left(i_{nt}|\beta, x_{nit}\right)\left(1-\psi_r I^{\text{SBA}}_{x_{knit}}\right) + \psi_r I^{\text{SBA}}_{x_{knit}} = 1$ when $\psi_{r=1}$). In all other situations the probability simplifies back to $\Pr\left(i_{nt}|\beta, x_{nit}\right)$. As in the case of the EBA-like model, in the case where $I^{\text{SBA}}_{x_{kn\forall jt}} = 1$, the choice probabilities are obtained using the MNL model.

As mentioned above, while a respondent's true consideration set cannot be known with certainty, observed choice behaviour helps make probabilistic statements about the likelihood of competing consideration sets being the true choice set. In this case, the (unconditional) probabilities are denoted by π_r. Specifically, $\pi_{r=1}$, which relates to $\psi_{r=1}$, represents the (unconditional) probability that respondents limited their choice task to those containing attribute level l_k^{SBA}. Conversely, $\psi_{r=0}$, which is linked with $\psi_{r=0}$, denotes the (unconditional) probability that respondents do not exhibit SBA-like behaviour. Again, these probabilities, along with the attribute parameters, are retrieved using maximum likelihood estimation.

2.3. Accounting for both EBA-like and SBA-like choice behaviours

Despite the advantages of accounting for either EBA or SBA in choice models, there may be situations where respondents may actually exhibit both choice behaviours. In such cases, not accommodating for both types of behaviour 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.

To account for situations where respondents exhibit both SBA-like and EBA-like behaviour and assuming that l_k^{EBA} and l_k^{SBA} both relate to the levels of the same attribute, k (i.e., so that they cannot both be present in the same alternative), the expressions in Eqs. (4a) and (5a) can be combined to take the following generalised form:

$$\Pr\left(y_n|\beta,\pi,x_n\right) = \sum_{c=1}^{C=4} \pi_c \prod_{t=1}^{T_n} \left(\Pr\left(i_{nt}|\beta,x_{nit}\right)\left(1-\psi_r I_{x_{knit}}^{\text{SBA}}\right)+\psi_r I_{x_{knit}}^{\text{SBA}}\right)\left(1-\psi_q I_{x_{knit}}^{\text{EBA}}\right), \tag{6a}$$

where the indicator variables, $I_{x_{knit}}^{\text{EBA}}$, $I_{x_{knit}}^{\text{SBA}}$, and discrete variables, ψ_q and ψ_r, are defined as above, and where C denotes and the number of combinations of EBA-like and SBA-like behaviour. In this case, $C = 4$:

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

Again, probabilistic estimates are obtained for each of the four individual behavioural rules. These are represented by π_{q_0,r_0}, π_{q_1,r_0}, π_{q_0,r_1} and π_{q_1,r_1} respectively.

2.4. 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:

$$\Pr\left(y_n|\beta,\pi,x_n\right) = \sum_{c=1}^{C} \pi_c \prod_{t=1}^{T_n} \left(\Pr\left(i_{nt}|\beta_s,x_{nit}\right)\left(1-\psi_q I_{x_{knit}}^{\text{SBA}}\right)+\psi_q I_{x_{knit}}^{\text{SBA}}\right)\left(1-\psi_r I_{x_{knit}}^{\text{EBA}}\right), \tag{7}$$

where C now encompasses the number of latent segments on the basis of preferences (i.e., $C = Q \times R \times S$, where S denotes the number of preference classes). We highlight that the expression Eq. (7) 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. (4); when $R = 2$ and $Q = S = 1$ it is the same as the SBA-like model outlined in Eq. (5); in the case where $Q = R = 2$ and $S = 1$ it describes the combined model given in Eq. (6); and with $Q = R = 1$ and $S > 1$ it represents a standard latent class model. In our analysis we report the results from these models.

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.

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

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).

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 analysis of the data from a pilot study of 648 observations (collected from 54 respondents). The final design consisted of five blocks, each having 12 choice tasks. For each choice task, respondents were asked to choose between two hypothetical innovation scenarios and a 'none' option. An example choice task is presented in Figure 1.

Which ONE of the following innovations would you prefer your local NHS to spend its budget on?

	Option 1	**Option 2**	**Option 3**
People	Disabled people	Obese	
Age group	Elderly (more than 65)	Young (less than 18)	
Time to get into the NHS	6–12 months	0–5 months	
Whether it works	Experts say it works elsewhere in the NHS	It works and scientific studies confirm this	None of them
Potential health gain	0 **75** 100 Good health	0 **50** 100 Moderate health	
Cost to you (£/month)	£40	£10	
Tick the ONE you prefer the most	☐	☐	☐

Figure 1. Choice task example

Using a postal survey, a total of 7,218 observations for model estimation were gathered from a sample of 594 respondents, each of whom answered 12 choice tasks. Most respondents in our sample were female (61 percent), with an average age of 50 years, and the majority of them described themselves as 'white' (87 percent). Approximately 30 percent were retired and 28 percent were employed full-time. A comparison against the 2011 UK census data suggests that our sample was broadly in line with the West Yorkshire population, albeit slightly older than the regional average (40 years) and more likely to be retired (West Yorkshire average of 15 percent).

4. Results

We begin this section with the results obtained from the discrete choice models outlined in Section 2. Following this, we compare the marginal willingness to pay (WTP) estimates under the different model assumptions.

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 and labelled as Model 1, almost all parameter estimates are statistically significant, and are in line with our expectations. 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'.[1]

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-like and SBA-like behaviour. Subsequently, we concurrently account for preference heterogeneity. In total, we estimate eight models.

Referring back to Table 2, it is obvious that a move from Model 1 to Model 2 leads to a dramatic improvement in model fit (by over 700 log-likelihood units at the expense of one additional parameter). We draw attention to the significant share of respondents predicted as having eliminated alternatives aimed at addressing 'drug addiction' or 'obesity'. We observe that around 17 percent of the respondents adopted this processing strategy. Similar to Model 1, results obtained in Model 2 indicate that 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' and 'obesity' levels appear to be relatively less extreme. This reinforces the necessity of accounting for this type of behaviour.

These findings also hold in Model 3, which accommodates a different set of individual behavioural rules. Model 3 allows for the fact that respondents select innovation alternatives based on whether it targets cancer patients or not. In fact, according to the results, approximately 64 percent of the respondents exhibit this SBA-like behaviour. Importantly, accounting for this type of behaviour also seems to improve the model fit, when compared to the case where conventional random utility maximisation is assumed (i.e., Model 1). We also witness a sharp decline in the relative magnitude of the

[1] We note that in all models the levels of the qualitative variables are included with the constraint that $\sum_l^L \beta_l = 0$. To facilitate interpretation, we report coefficients for all levels and their associated t-ratios. We note, though, that the number of parameters and the information criteria measures reported in Tables 2 and 3 account for these constraints.

Table 2. Estimation results (preference homogeneity)

	Model 1		Model 2		Model 3		Model 4	
	est.	$\lvert t\text{-rat.}\rvert$	est.	$\lvert t\text{-rat.}\rvert$	est.	$\lvert t\text{-rat.}\rvert$	est.	$\lvert t\text{-rat.}\rvert$
$\hat{\beta}_{cost}$	-0.011	8.17	-0.012	8.21	-0.011	7.80	-0.011	7.96
$\hat{\beta}_{eveff_{nosci}}$	-0.231	9.28	-0.225	8.68	-0.230	9.11	-0.226	8.64
$\hat{\beta}_{eveff_{sci}}$	0.176	7.90	0.175	7.64	0.184	8.08	0.181	7.75
$\hat{\beta}_{eveff_{expert}}$	0.055	2.42	0.050	2.13	0.046	1.96	0.045	1.87
$\hat{\beta}_{healthg_{50}}$	-0.301	12.08	-0.309	11.90	-0.302	11.89	-0.310	11.80
$\hat{\beta}_{healthg_{75}}$	0.090	4.05	0.093	4.12	0.088	3.92	0.091	4.00
$\hat{\beta}_{healthg_{100}}$	0.211	9.14	0.216	9.00	0.213	8.98	0.218	8.93
$\hat{\beta}_{imptime_{0-5}}$	0.068	3.08	0.066	2.90	0.074	3.26	0.069	3.01
$\hat{\beta}_{imptime_{6-12}}$	-0.012	0.52	-0.009	0.41	-0.020	0.88	-0.015	0.65
$\hat{\beta}_{imptime_{12}}$	-0.056	2.49	-0.056	2.44	-0.054	2.34	-0.054	2.32
$\hat{\beta}_{targeta_{young}}$	0.097	4.05	0.095	3.85	0.099	4.13	0.098	3.95
$\hat{\beta}_{targeta_{adult}}$	0.157	6.36	0.163	6.39	0.159	6.39	0.163	6.34
$\hat{\beta}_{targeta_{elderly}}$	-0.254	10.86	-0.258	10.86	-0.258	10.97	-0.261	10.93
$\hat{\beta}_{targetp_{disabled}}$	0.466	11.03	0.375	8.38	0.712	11.04	0.546	6.95
$\hat{\beta}_{targetp_{drug}}$	-1.351	26.15	-1.218	20.99	-1.105	15.66	-1.053	12.34
$\hat{\beta}_{targetp_{cancer}}$	1.379	16.67	1.343	15.12	0.117	0.44	0.476	1.39
$\hat{\beta}_{targetp_{mental}}$	0.327	5.46	0.289	4.33	0.592	7.31	0.476	4.84
$\hat{\beta}_{targetp_{obese}}$	-0.955	19.43	-0.805	14.87	-0.710	10.25	-0.643	7.71
$\hat{\beta}_{targetp_{asthma}}$	0.133	2.32	0.016	0.26	0.395	5.08	0.199	2.13
$\hat{\beta}_{ASC_{hypoth}}$	0.781	29.22	1.066	34.49	0.654	17.89	0.978	21.62
$\hat{\beta}_{ASC_{none}}$	-0.781	29.22	-1.066	34.49	-0.654	17.89	-0.978	21.62
π_{r_0,c_0}	1.000	fixed	0.827	52.37	0.363	6.32	0.406	3.97
π_{r_1,c_0}			0.173	10.94			0.041	2.07
π_{r_0,c_1}					0.637	11.08	0.421	4.11
π_{r_1,c_1}							0.131	5.69
$LL(\hat{\beta})$	-6,390.409		-5,672.681		-6,381.366		-5,668.292	
K	15		16		16		18	
$\bar{\rho}^2$	0.182		0.274		0.183		0.274	
AIC	12,811.154		11,377.714		12,794.760		11,372.724	
BIC	12,913.798		11,487.485		12,904.531		11,496.038	
$CAIC$	12,928.766		11,503.166		12,920.926		11,514.571	

'cancer' coefficient. Indeed, we now see that, while positive, it is no longer significantly different from zero. On this basis, the coefficient retrieved for this level in Model 1 would appear to be considerably upwardly biased.

Given the importance of the results from Models 2 and 3, Model 4 accommodates situations in which respondents adopt one or more of the individual behavioural rules captured in Models 2 and 3. Accommodating for all four individual behavioural rules concurrently reveals that the model fit is superior to all previous models. Again, we remark some changes in the relative magnitudes of the coefficients pertaining to the target population attribute. Crucially, though, we find that only 41 percent of the respondents based their choices on conventional RUM. The remaining 59 percent used an EBA-like and/or SBA-like decision-making heuristic. 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.

Comparable to Model 2, we find that just over 17 percent of respondents exhibited EBA-like behaviour. Interestingly, though, the majority of these respondents (over three-quarters) also exhibited SBA-like behaviour. In total, we find that approximately 55 percent of respondents used a SBA-like strategy when the choice task contained the 'cancer' level. In this case, however, the majority of these respondents did not exhibit any EBA-like behaviour. In fact, of all the individual behavioural rules, the highest proportion used only a SBA-like decision-making heuristic. This is more clearly illustrated in the mosaic plot in Figure 2. Compared to the previous models, Model 4 appears better suited to uncovering respondents' behaviour. The fact that the proportion exhibiting each behavioural rule is non-trivial, it also raises some concerns about the appropriateness of assuming deterministically not accounting for all possible rules simultaneously.

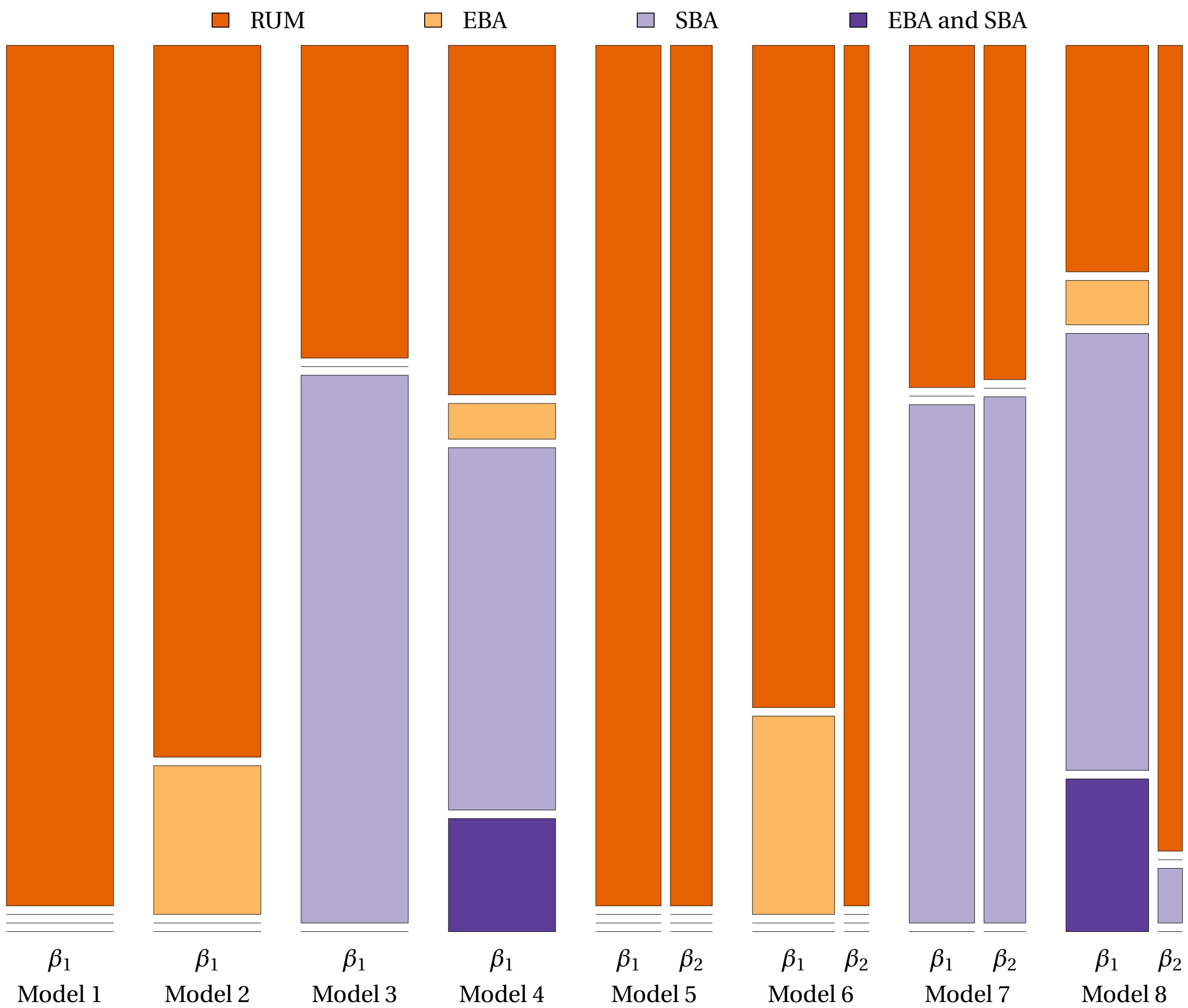

Figure 2. Predicted choice behaviours adopted by respondents

Because it might be unrealistic to assume homogeneity of preferences, and the potential risk of confounding between preference heterogeneity and choice behaviour, we estimate additional models.

These are based on the same individual behavioural rules used in Models 1–4, but where we assume that there are two latent classes of preferences.[2] Results from these models are reported in Table 3.

Table 3. Estimation results (preference heterogeneity)

	Model 5		Model 6		Model 7		Model 8	
	est.	|t-rat.|	est.	|t-rat.|	est.	|t-rat.|	est.	|t-rat.|
$\hat{\beta}_{1cost}$	-0.009	5.02	-0.009	5.36	-0.009	4.84	-0.009	5.09
$\hat{\beta}_{1eveff_{nosci}}$	-0.243	7.41	-0.260	7.89	-0.246	7.38	-0.268	8.00
$\hat{\beta}_{1eveff_{sci}}$	0.173	5.86	0.195	6.83	0.181	5.91	0.210	7.02
$\hat{\beta}_{1eveff_{expert}}$	0.070	2.45	0.065	2.33	0.066	2.21	0.059	2.04
$\hat{\beta}_{1healthg_{50}}$	-0.325	9.51	-0.330	9.56	-0.330	9.48	-0.339	9.66
$\hat{\beta}_{1healthg_{75}}$	0.104	3.73	0.109	4.06	0.102	3.65	0.106	3.93
$\hat{\beta}_{1healthg_{100}}$	0.222	7.12	0.220	6.97	0.227	7.09	0.233	7.04
$\hat{\beta}_{1imptime_{0-5}}$	0.072	2.61	0.069	2.58	0.078	2.73	0.076	2.77
$\hat{\beta}_{1imptime_{6-12}}$	-0.015	0.53	0.002	0.07	-0.022	0.76	-0.009	0.33
$\hat{\beta}_{1imptime_{12}}$	-0.058	2.06	-0.071	2.59	-0.056	1.97	-0.066	2.39
$\hat{\beta}_{1targeta_{young}}$	0.116	3.66	0.119	3.88	0.120	3.72	0.127	4.08
$\hat{\beta}_{1targeta_{adult}}$	0.129	4.01	0.127	4.08	0.129	3.94	0.123	3.88
$\hat{\beta}_{1targeta_{elderly}}$	-0.245	8.15	-0.246	8.46	-0.248	8.16	-0.250	8.53
$\hat{\beta}_{1targetp_{disabled}}$	0.308	5.11	0.379	5.75	0.522	4.56	0.646	5.69
$\hat{\beta}_{1targetp_{drug}}$	-1.199	14.26	-1.329	11.16	-0.991	7.85	-1.095	6.43
$\hat{\beta}_{1targetp_{cancer}}$	1.301	10.96	1.398	11.58	0.207	0.40	0.049	0.09
$\hat{\beta}_{1targetp_{mental}}$	0.314	3.25	0.368	3.46	0.548	3.74	0.688	4.46
$\hat{\beta}_{1targetp_{obese}}$	-0.862	11.40	-0.954	10.43	-0.657	5.28	-0.725	4.93
$\hat{\beta}_{1targetp_{asthma}}$	0.138	1.58	0.138	1.51	0.371	2.67	0.437	3.18
$\hat{\beta}_{1ASC_{hypoth}}$	1.784	20.84	1.948	9.30	1.670	17.21	1.795	8.27
$\hat{\beta}_{1ASC_{none}}$	-1.784	20.84	-1.948	9.30	-1.670	17.21	-1.795	8.27
$\hat{\beta}_{2cost}$	-0.018	6.93	-0.024	5.36	-0.017	6.53	-0.025	5.06
$\hat{\beta}_{2eveff_{nosci}}$	-0.246	5.06	-0.208	3.35	-0.242	4.86	-0.207	3.28
$\hat{\beta}_{2eveff_{sci}}$	0.231	5.35	0.209	3.60	0.242	5.45	0.208	3.50
$\hat{\beta}_{2eveff_{expert}}$	0.015	0.35	-0.001	0.01	-0.001	0.01	-0.000	0.00
$\hat{\beta}_{2healthg_{50}}$	-0.331	6.91	-0.388	6.06	-0.330	6.69	-0.385	5.90
$\hat{\beta}_{2healthg_{75}}$	0.086	2.02	0.051	0.93	0.085	1.94	0.047	0.84
$\hat{\beta}_{2healthg_{100}}$	0.245	5.54	0.337	5.88	0.245	5.37	0.338	5.75
$\hat{\beta}_{2imptime_{0-5}}$	0.063	1.48	0.094	1.70	0.070	1.60	0.094	1.67
$\hat{\beta}_{2imptime_{6-12}}$	-0.016	0.36	-0.078	1.37	-0.028	0.63	-0.077	1.33

Continued on next page

[2] 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 a combined latent class random parameters logit. We suggest that these represent interesting extensions to our approach.

Table 3: Estimation results (preference heterogeneity) (cont'd)

	Model 5		Model 6		Model 7		Model 8	
	est.	$\lvert t$-rat.$\rvert$	est.	$\lvert t$-rat.$\rvert$	est.	$\lvert t$-rat.$\rvert$	est.	$\lvert t$-rat.$\rvert$
$\hat{\beta}_{2imptime_{12}}$	-0.047	1.07	-0.016	0.29	-0.042	0.91	-0.017	0.30
$\hat{\beta}_{2targeta_{young}}$	0.103	2.10	0.097	1.41	0.107	2.17	0.103	1.46
$\hat{\beta}_{2targeta_{adult}}$	0.189	3.86	0.204	3.20	0.192	3.90	0.205	3.13
$\hat{\beta}_{2targeta_{elderly}}$	-0.291	5.81	-0.301	3.93	-0.299	5.87	-0.308	3.80
$\hat{\beta}_{2targetp_{disabled}}$	0.844	11.17	0.426	3.95	1.087	11.08	0.435	3.06
$\hat{\beta}_{2targetp_{drug}}$	-2.071	17.69	-1.290	7.18	-1.836	14.07	-1.264	6.03
$\hat{\beta}_{2targetp_{cancer}}$	1.721	13.27	1.445	8.74	0.480	1.42	1.384	3.05
$\hat{\beta}_{2targetp_{mental}}$	0.558	6.19	0.247	1.70	0.821	7.22	0.248	1.33
$\hat{\beta}_{2targetp_{obese}}$	-1.326	13.28	-0.633	4.86	-1.084	9.21	-0.605	3.72
$\hat{\beta}_{2targetp_{asthma}}$	0.274	2.95	-0.195	1.27	0.531	4.64	-0.197	1.03
$\hat{\beta}_{2ASC_{hypoth}}$	0.236	5.12	0.452	6.43	0.106	1.82	0.439	5.22
$\hat{\beta}_{2ASC_{none}}$	-0.236	5.12	-0.452	6.43	-0.106	1.82	-0.439	5.22
π_{q_1,r_0,c_0}	0.609	24.94	0.590	13.08	0.242	2.82	0.203	2.74
π_{q_1,r_1,c_0}			0.177	11.20			0.040	2.01
π_{q_1,r_0,c_1}					0.367	4.28	0.392	5.74
π_{q_1,r_1,c_1}							0.137	5.97
π_{q_2,r_0,c_0}	0.391	16.03	0.234	5.25	0.152	4.93	0.214	2.42
π_{q_2,r_1,c_0}			0.000	0.00			0.000	0.01
π_{q_2,r_0,c_1}					0.239	7.40	0.015	0.18
π_{q_2,r_1,c_1}							0.000	0.00
$LL(\hat{\beta})$	-5,854.472		-5,352.373		-5,846.307		-5,349.261	
K	31		33		33		37	
$\bar{\rho}^2$	0.248		0.312		0.249		0.312	
AIC	11,770.943		10,770.746		11,758.613		10,772.523	
BIC	11,983.969		10,997.515		11,985.382		11,026.779	
$CAIC$	12,014.969		11,030.515		12,018.382		11,063.779	

From the results of Model 5, 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 discussed earlier. 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 Model 5 to that obtained under Model 1, we demonstrate the importance of accounting for preference heterogeneity. However, we find that when compared to those that account for EBA-like behaviour, the model fit achieved under Model 5 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 perhaps SBA rather than solely addressing unobserved preference heterogeneity.

Turning our attention to Model 6, which accommodates EBA-like behaviour, we again find evidence of heterogeneous preferences towards health service innovations. Interestingly, though, the size of the preference segments is different compared to Model 5. Although Model 5 suggests that the majority of respondents based their choices on the RUM individual behavioural rule, there is a minority group (18 per cent) who made their choices by eliminating alternatives that contained 'unfavourable' levels of the target population attribute. It is interesting to remark that this subset all shared the same preferences. The results suggest that no respondents in the second (smaller) segment (23 percent of respondents) exhibited EBA-like behaviour. This pattern is clear to see in the mosaic plot in Figure 2. In terms of model fit, we observe an improvement of over 400 log-likelihood units compared to its preference homogeneity counterpart (Model 2). 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.

Results from Model 7 also reveal preference heterogeneity and a high incidence of respondents who used a SBA-like decision rule. In this case we observe that around 39 percent of the respondents base their decisions on the conventional RUM behavioural rule. This means that we once more find that the majority of respondents adopted SBA-like criterion when making their choices. We remark that under Model 7 the proportions predicted as having adopted both types of behavioural rule are broadly analogous with those retrieved in its preference homogeneity equivalent (Model 3). As also shown graphically in the mosaic plot, it is interesting to note that approximately the same proportion (c.60 percent) within each preference segment used this behavioural rule. Nevertheless, the model fit is substantially better when the heterogeneity in respondents' preferences are accounted for.

The final model, Model 8, is similar to Model 4 in that it accommodates all four individual behavioural rules concurrently, but that it also takes preference heterogeneity into account. As can be seen, this final model achieves the highest model fit. On this basis, this model can be considered as the model that best explains respondents' individual behavioural rules and preferences. According to the results, 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 random utility maximisation 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. Returning again to Figure 2, the different individual rules adopted by each segment of preferences is apparent.

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. As portrayed in Figure 2, 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, we compare the marginal WTP estimates (against a baseline attribute level) derived under all eight models. We note that to ease comparison, in the cases of Models 5–8, we have weighted the marginal WTP according to the unconditional class membership probabilities associated with each set of preferences (and, thus, the estimates represent the most likely marginal WTP within in the sample).

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 (Model 1) to the model that accounts for a range of processing strategies and preference heterogeneity (Model 8). 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 Tables 2 and 3, 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 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, the result that respondents dislike spending on people with 'drug addiction', 'obesity', and 'asthma' and are willing to pay more on for innovations targeting 'cancer patients' and 'disabled generally holds across Models 1–8. 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.

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 (Models 2 and 4 versus Models 1 and 3) and heterogeneous (Models 6 and 8 versus Models 5 and 7) preferences. This is not surprising given the fact that the marginal WTP estimates obtained from the models that account for this EBA-like behaviour (Models 2, 4, 6 and 8) effectively only applies to the subset who did not adopt this processing strategy.[3] This led to the slight increase in marginal WTP.

[3] 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.

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

	Model 1	Model 2	Model 3	Model 4	Model 5[b]	Model 6[b]	Model 7[b]	Model1 8[b]
$\hat{WTP}_{eveff_{nosci}}$	-36.31	-34.51	-38.03	-35.93	-38.31	-41.35	-40.24	-44.76
	(-47.87,-24.75)	(-45.65,-23.37)	(-50.62,-25.44)	(-47.83,-24.04)	(-51.66,-24.97)	(-57.24,-25.47)	(-51.86,-28.62)	(-67.92,-21.60)
$\hat{WTP}_{eveff_{expert}}$	-10.72	-10.77	-12.63	-12.03	-11.58	-12.61	-13.40	-14.86
	(-17.73,-3.72)	(-17.69,-3.86)	(-20.36,-4.89)	(-19.47,-4.59)	(-18.85,-4.32)	(-20.78,-4.45)	(-20.61,-6.20)	(-26.49,-3.24)
$\hat{WTP}_{healthg_{75}}$	34.91	34.71	35.80	35.39	37.84	40.26	38.99	42.12
	(23.60,46.21)	(23.56,45.85)	(23.82,47.79)	(23.77,47.02)	(24.34,51.34)	(24.90,55.62)	(27.69,50.30)	(20.72,63.51)
$\hat{WTP}_{healthg_{100}}$	45.77	45.28	47.31	46.60	49.22	52.15	51.22	55.62
	(32.65,58.88)	(32.38,58.17)	(33.05,61.57)	(32.85,60.34)	(33.27,65.16)	(34.15,70.15)	(37.77,64.67)	(29.84,81.39)
$\hat{WTP}_{imptime_{6-12}}$	-7.12	-6.47	-8.65	-7.44	-7.54	-7.14	-9.03	-8.82
	(-14.02,-0.21)	(-13.25,0.31)	(-16.13,-1.17)	(-14.62,-0.26)	(-14.72,-0.36)	(-14.80,0.52)	(-15.94,-2.12)	(-19.13,1.48)
$\hat{WTP}_{imptime_{12}}$	-11.11	-10.52	-11.76	-10.91	-11.12	-12.51	-11.69	-13.17
	(-18.30,-3.93)	(-17.57,-3.47)	(-19.37,-4.16)	(-18.24,-3.58)	(-18.66,-3.59)	(-20.92,-4.10)	(-18.70,-4.68)	(-24.32,-2.03)
$\hat{WTP}_{targeta_{young}}$	31.33	30.49	32.83	31.66	32.81	33.86	34.39	36.05
	(21.09,41.56)	(20.51,40.47)	(21.78,43.88)	(21.09,42.23)	(20.97,44.65)	(20.89,46.83)	(24.11,44.68)	(17.48,54.61)
$\hat{WTP}_{targeta_{adult}}$	36.71	36.36	38.28	37.34	35.60	35.52	36.94	36.63
	(24.52,48.90)	(24.30,48.42)	(25.27,51.30)	(24.73,49.95)	(22.14,49.07)	(20.73,50.30)	(25.39,48.49)	(16.46,56.80)
$\hat{WTP}_{targetp_{disabled}}$	12.39	7.47	11.07	6.15	5.87	2.55	4.21	-1.90
	(-2.32,27.10)	(-7.70,22.63)	(-4.16,26.29)	(-9.50,21.80)	(-10.73,22.47)	(-16.74,21.85)	(-9.51,17.92)	(-27.48,23.68)
$\hat{WTP}_{targetp_{drug}}$	-149.77	-130.08	-155.87	-134.85	-159.03	-154.27	-165.70	-166.67
	(-186.08,-113.45)	(-161.58,-98.58)	(-195.94,-115.80)	(-169.01,-100.68)	(-199.05,-119.01)	(-204.02,-104.51)	(-204.19,-127.20)	(-241.06,-92.27)
$\hat{WTP}_{targetp_{cancer}}$	93.96	91.00	-43.61	0.00	91.53	96.09	-31.14	-44.30
	(64.66,123.27)	(61.19,120.81)	(-103.45,16.24)	(-72.36,72.36)	(56.66,126.40)	(54.09,138.09)	(-92.37,30.09)	(-184.10,95.51)
$\hat{WTP}_{targetp_{obese}}$	-114.46	-94.43	-119.59	-98.69	-120.08	-117.16	-125.76	-128.84
	(-143.74,-85.17)	(-119.54,-69.33)	(-152.14,-87.05)	(-126.18,-71.21)	(-152.67,-87.49)	(-158.16,-76.16)	(-156.03,-95.49)	(-191.50,-66.18)
$\hat{WTP}_{targetp_{asthma}}$	-17.31	-23.52	-18.06	-24.41	-18.05	-23.18	-18.73	-25.65
	(-32.57,-2.05)	(-39.43,-7.61)	(-34.02,-2.10)	(-40.93,-7.89)	(-35.95,-0.14)	(-43.11,-3.24)	(-33.15,-4.31)	(-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.

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 (Models 3 and 4 versus Models 1 and 2) and heterogeneous (Models 7 and 8 versus Models 5 and 6) specifications. Again, this reflects the fact that the coefficients uncovered from the SBA-like models (Models 3, 4, 7 and 8) are actually based on the choices made by respondents who did not use this decision-making strategy.[4] 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. Interestingly, when the SBA-like behaviour has been accounted for, we actually find evidence that suggests the average respondents' marginal WTP within the sample for targeting 'cancer patients' may not be significantly different from the marginal WTP estimates of any other target population levels.

Notwithstanding the notable differences in the marginal WTP estimates obtained from the eight 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 some of the eight models.

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-like and SBA-like behaviour 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 reveal a significant portion (17 percent) of respondents exhibited this EBA-like behaviour: they eliminated from their choice sets all alternatives targeting either 'obesity' or 'drug addiction'. Similarly, SBA-like behaviour was common (up to 60 percent of respondents) as they only selected among alternatives (when available) that ensured 'cancer patients' would be targeted. Accommodating EBA-like and SBA-like choice behaviour concurrently proved to give a richer insight into respondents' behaviour

[4] 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.

and suggested that as few as 40 percent of respondents adopted the conventional RUM decision rule. In line with previous studies, we found that assuming homogeneous preferences in respondents was inappropriate. Going beyond this, we also show that each segment of respondents differed in their preferences, but they also adopted different decision-making heuristics. We generally only found the EBA-like and SBA-like behaviour(s) exhibited by those in the largest preference segment. Within the smallest subset of respondents (based on preferences), we observe that only a minority of them did not use the conventional random utility decision rule.

To conclude, failing to account for EBA-like and/or SBA-like choice behaviours was not optimal and have implications for WTP estimates. Where our models accounted for such behaviours they outperformed those based solely on the random utility maximisation assumption. Although there are a large number of other decision-making heuristics and processing strategies that can also be considered and there is the potential to uncover additional random taste variation, the models illustrated here provide additional insight into the manner in which respondents arrive at their final decision. This represents an exciting research challenge.

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