Attribute-level non-attendance in a choice experiment
investigating preferences for health service innovations

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Abstract
An extensive literature has established that it is common for respondents to ignore attributes of the alternatives within choice experiments. In most of these attribute non-attendance (ANA) studies, it is assumed that respondents consciously (or unconsciously) ignore one or more attributes of the alternatives, regardless of its levels. In this paper, we present a new line of enquiry and approach for modelling non-attendance in the context of investigating preferences for health service innovations. This approach recognises that non-attendance may not just be associated with attributes but may also apply to the attribute's levels. Our results show that respondents process each level of an attribute differently: while attending to the attribute, they ignore a subset of the attribute's levels. In such cases the usual approach of assuming that respondents either attend to the attribute or not, irrespective of its levels, is erroneous and could lead to misguided policy recommendations. Our results indicate that allowing for attribute-level non-attendance leads to substantial improvements in the model fit and does have impacts for willingness to pay estimations.

Keywords: discrete choice experiments; attribute non-attendance; attribute-level non-attendance; discrete mixture; health service innovations.

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1. Introduction

In health care systems where the number of innovations that can be implemented outstrips scarce resources, prioritisation surrounding which health service innovations receive resources is inevitable. Alongside other methods used by decision-makers and health economists to inform such decisions, discrete choice experiments (DCE) have been applied to assess preferences and valuations of health service users and providers for various innovations (e.g., Ryan and Hughes, 1997; Watson et al., 2004; Lancsar et al., 2007; Marshall et al., 2007; Green and Gerard, 2009; Guo et al., 2011). This stated preference elicitation technique is de-compositional and based on the assumption that health care innovations, services or policies, can be described by their attributes, and individuals make choices between alternatives varying in terms of the levels of these attributes. The choices made reveal values individuals attach to the attributes of innovations and various innovation options.

A typical assumption of the DCE is that respondents consider all attributes when making trade-offs between them to choose their preferred alternative. However, recent studies in the fields of environment economics (e.g., Campbell et al., 2008; Scarpa et al., 2009; Carlsson et al., 2010; Campbell et al., 2011; Scarpa et al., 2013), transport economics (e.g., Hensher et al., 2005; Hensher, 2006; Hensher, Rose and Greene, 2012; Hess and Hensher, 2013), and health economics (e.g., Scott, 2002; Ryan et al., 2009; Hole, 2011a,b; Hole et al., 2012; Lagarde, 2012) have recognised that when discrete choices are made, only a subset of at the attributes are traded-off or considered by respondents. This is widely referred as attribute non-attendance (ANA) (e.g., Scarpa et al., 2009) or the ignoring of attributes (e.g., Hensher et al., 2005). Some of the underlying reasons for this phenomenon include, *inter alia*, (i) a genuine disinterest in the attribute, (ii) the context and survey design related issues, such as complexity, controversy and sensitivity of the survey topic, irrelevance of the attribute to respondents, cognitive demand required to complete choice tasks, (iii) respondents’ different capabilities and motivations (Hensher et al., 2005), and (iv) strategic behaviour respondents may exhibit, especially
in public policy choices, such as innovation prioritisation in a publicly-funded healthcare system.

Notwithstanding the recent extension of the analysis of ANA in health choice experiments, the topic has largely been overlooked by health economists. Nevertheless, ANA in health DCEs is potentially highly relevant. Indeed, as suggested by Lagarde (2012), it would not be surprising for respondents within health related choice experiments to use lexicographic preference orderings for potentially strong and sensitive attributes, such as health impacts/outcomes.

The typical assumption within the ANA related literature is that respondents consciously (or unconsciously) either attend to or do not attend to a particular attribute, irrespective of its levels. However, in cases where attribute levels are qualitative and distinct, which is a common practice in health related discrete choice experiments (DCEs) (e.g., Ryan et al., 2001; Phillips et al., 2002; Gerard et al., 2003; Bennett and Savani, 2004; Fraenkel et al., 2004; Gerard and Lattimer, 2005; Mantovani et al., 2005; Kellett et al., 2006; Marshall et al., 2007; Ryan and Watson, 2009; Watson et al., 2011; Hole and Kolstad, 2012; Cunningham et al., 2013; Lynn et al., 2013) it is possible that respondents, while attending to the attribute, actually ignore a subset of the attribute’s levels. In this case, assuming that non-attendance applies to the whole attribute would be erroneous and could lead to misguided policy recommendations.

In this paper we investigate both attribute non-attendance (ANA) and non-attendance to levels of attributes, which we term ‘attribute-level non-attendance’ (ALNA), using data obtained from a DCE survey administered in West Yorkshire, UK. The DCE explored preferences relating to health service innovations, ‘new ideas, practices, and services’, that local health service providers should prioritise investing in. Innovations differed in terms of six characteristics: (i) target population; (ii) target age group; (iii) implementation time; (iv) the certainty of their likely effects; (v) potential health benefits; and, (vi) cost to the taxpayer. While we address ANA for all attributes, we explore ALNA for the six qualitative (i.e., categorical) levels of the ‘target population’ attribute: (i) obesity; (ii) disability; (iii) asthma; (iv) cancer; (v) substance addiction; and, (vi) mental health problems.

The propensity to ignore attribute-levels has the same reasoning behind it as ignoring the attribute itself. In addition to aforementioned reasons, the (perceived) controversy involved in
the context of the experiment (i.e., prioritisation of health service innovations) may also result in some attribute levels being ignored as a form of ‘protest’ or ‘strategic’ behaviour. For example, asking members of the general public to choose between different innovation options that will mostly benefit one population group in society (whilst imposing an opportunity cost on other groups in society), may be perceived as contrary to the ‘equality’ of a health care system, especially since health care is a public good that individuals contribute towards via their tax. It is also apparent that some health conditions have significant impact on the public over time, and thus, may require high prioritisation actions around these issues to alleviate their impact. However, although there may be a medical need, some of these prioritisation actions may be perceived differently by the general public. For instance, obesity is one of the health problems receiving increasing attention in the UK. The clinical guidelines 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). Despite this, the public have mixed views about investing in obesity treatments, which will be supported by their tax contributions. While some people believe that the obesity is “self-inflicted” and dislike spending on treatments targeting people with obesity (e.g., Lund et al., 2011), others believe that obesity is not merely a lifestyle choice and there should be equal health care access to those who are struggling with it (e.g., Chambers and Traill, 2011; Sikorski et al., 2012). Due to such varying attitudes to different health problems, it is not realistic to assume that individuals consider innovations targeting different population groups in the same way. For example, while some people may find it irrelevant whether or not an innovation targets people with obesity, they might still take into account if the innovation focuses on cancer patients or substance users. Others might ignore all target groups when making innovation investment choices. This may then imply that they ignore the attribute completely and thus exhibit the ‘typical’ ANA behaviour. This makes it important for the analysis of choice data to accommodate for such behaviour and is the reason why we focus on the ‘target population’ attribute. Failing to account for this type of processing heterogeneity is likely to be suboptimal.
This paper intends to highlight the importance of and need for identifying ALNA for qualitative attribute-levels, and thus contributes to the stated preference literature that has raised the issues involved in non-attendance to attribute-levels (e.g., Campbell et al., 2012). Furthermore, the method outlined in this paper provides a step forward on how to analyse ‘attribute-level’ non-attendance in the stated preference methodology using discrete mixture logit (DML) models. In addition to this methodological contribution, the research presents a unique approach to exploring the public’s preferences for health service innovations. It involves viewing healthcare innovations in a broader perspective as ‘bundles’ of characteristics, rather than dealing with specific innovations in isolation, such as ‘orthopaedic services’. This allows policy-makers to compare numerous competing health service innovations.

Overall, our findings show that: (1) many respondents do not consider health service innovation attributes fully; (2) while 66 percent of the respondents consider the ‘target population’ when making choices, different shares of respondents consider different target groups (e.g., 18 percent take into account whether the innovation is targeting people with obesity, and 75 percent consider whether the innovation is for ‘cancer patients’); (3) the gains in model fit are substantial when accommodating ALNA; and (4) accommodating for both ANA and ALNA behaviour generally leads to a significant reduction in the marginal willingness to pay (WTP) estimates.

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

Following a random utility framework, the utility individual \( n \) obtains from choosing alternative \( i \), which is defined by \( K \) attributes, \( x_k \), where \( k = \{1, 2, 3, ..., K\} \), can be written as the following:

\[
U_{ni} = \sum_{k=1}^{K} \beta_k x_{nik} + \varepsilon_{ni},
\]
where $\beta_k$ are parameters to be estimated and $\epsilon_{ni}$ is an independent and identically distributed (IID) extreme value type 1 (EV1) error term, with constant variance of $\pi^2/6$. Given this assumption, the probability of choosing alternative $i$ from a total of $J$ alternatives—which is the probability that $U_{ni} > U_{nj} \forall j \neq i$—can be expressed as a multinomial logit (MNL) model:

$$
\Pr(U_{ni} > U_{nj} \forall j \neq i) = \Pr(i_n | x_n, \beta) = \frac{\exp\left(\sum_{k=1}^{K} \beta_k x_{nik}\right)}{\sum_{j=1}^{J} \exp\left(\sum_{k=1}^{K} \beta_k x_{njk}\right)}.
$$

(2)

Given the repeated nature of choice experiments, the specification can be easily generalised. In this case, the probability of a sequence of choices, i.e., $y_n = \langle i_{n1}, i_{n2}, \ldots, i_{nT_n} \rangle$, over the $T_n$ choice occasions for respondent $n$ takes the following form:

$$
\Pr(y_n | x_n, \beta) = \prod_{t=1}^{T_n} \frac{\exp\left(\sum_{k=1}^{K} \beta_k x_{nikt}\right)}{\sum_{j=1}^{J} \exp\left(\sum_{k=1}^{K} \beta_k x_{njkt}\right)}.
$$

(3)

While this MNL model directly uncovers estimates of respondents’ preferences, it does so in a manner that assumes that all respondents consider every attribute. However, a number of studies (e.g., Hensher et al., 2005; Campbell et al., 2008; Scarpa et al., 2009; Hess and Hensher, 2010; Carlsson et al., 2010; Hole, 2011a; Alemu et al., 2013) have established that a significant proportion of respondents ignore one or more of the attributes. It is, therefore, more appropriate to use a refined rationally adaptive model that is capable of accommodating different attribute-processing strategies. For this reason, models that impose probabilistic conditions on the utility expressions to accommodate for processing strategies should be considered. Such functional forms have the advantage of enabling the analyst to infer, up to a probability, the presence of processing strategies. This can be achieved using a discrete mixture logit (DML) model (see Hess et al., 2007; Train, 2008 for an overview and Hole, 2011a for an application to ANA).

In the DML modelling framework, non-attendance is captured by including a vector of dummy variables, $\alpha = \{\alpha_1, \alpha_2, \alpha_3, \ldots, \alpha_K\}$, in the model, where $\alpha_k = 1$ represents attendance to attribute $k$ and $\alpha_k = 0$ represents non-attendance. The $\alpha$ vector is unobserved, so the
objective of the analysis is to estimate the probability of observing different patterns of non-attendance. The probability of observing \( \alpha_k = 1 \) is denoted by \( \pi_k^1 \) and the probability of observing \( \alpha_k = 0 \) is denoted by \( \pi_k^0 \). The probabilities are subject to the following conditions:

\[
0 \leq \pi_k^0 \leq 1, \quad 0 \leq \pi_k^1 \leq 1, \quad \text{and} \quad \pi_k^0 + \pi_k^1 = 1.
\] (4)

The number of possible non-attendance patterns with \( K \) attributes is \( S = 2^K \). Each pattern, \( s = \{1, 2, 3, \ldots, S\} \), implies a different combination of zeros and ones in the \( \alpha \) vector, and the value of \( \alpha_k \) in combination \( s \) is denoted by \( \alpha_k^s \). The probability of observing combination \( s \) is the product of the probabilities of observing each \( \alpha_k^s \), and is denoted using \( \phi_s \). For example, the probability of observing \( \alpha^s = \{0, 1, 1, 0\} \), implying non-attendance to attribute 1 and 4 but not to attribute 2 and 3, is given by \( \phi_s = \pi_1^0 \times \pi_2^1 \times \pi_3^1 \times \pi_4^0 \).

The probability of choosing alternative \( i \), in Eq. 3 can then be rewritten as follows:

\[
\Pr \left( y_n | x_n, \beta, \pi \right) = \sum_{s=1}^{S=2^K} \phi_s \prod_{t=1}^T \exp \left( \sum_{k=1}^K \alpha_k^s \beta_k x_{nikt} \right) / \sum_{j=1}^J \exp \left( \sum_{k=1}^K \alpha_k^s \beta_k x_{njkt} \right). \] (5)

We acknowledge the similarity between the DML model and the latent class logit model, which also assumes finite representations of heterogeneity. In fact, the DML and latent class logit models are formally equivalent, the main difference being that in DML models the class sizes are not independent and the focus is usually on segmenting on a per parameter basis and not on the basis of the full set of parameters, which is typically the case in latent class models. Indeed, while the DML model expressed in Eq. 5 could be estimated using an equality-constrained latent class model where the values of \( \beta \) are assumed fixed and \( \phi \) are estimated independently (e.g. see Scarpa et al., 2009 and Campbell et al., 2011 for further details), we favour the behavioural appeal of retrieving probabilistic estimates for each parameter directly afforded by the DML approach.

Despite the advantages of this refined rationally adaptive model over the MNL model, it is only capable of identifying non-attendance at the attribute level and ignores the possibility that attendance might be dependent on the levels of the attribute in question. In other words,
the common assumption has been that if an attribute is not attended to by a respondent then
this takes place at every level of the attribute(s) in question. However, at least in principle,
one may postulate the hypothesis that, due to differences in priorities and preferences, there
is likely to be heterogeneity in the way respondents process the levels of attributes, especially
those with qualitative (or categorical)\(^1\) levels. Therefore, we further refine the rationally
adaptive model to account for ALNA.

The key difference between ANA and ALNA is that the discrete variables are associated
with the levels of the attribute(s) in question, rather than the attribute itself. For instance,
consider that the (qualitative) attribute of interest, \(k\), has \(L\) levels. In this case, the indirect
utility function for this attribute under our ANA model is expressed as:

\[
V_k = \alpha_k \sum_{l=1}^{L} \beta_k l x_{k l},
\]

(6)

where subscripts \(n, i\) and \(t\) are removed to reduce clutter. In the case of ALNA, we retrieve
separate probabilities of attendance for each of the levels:

\[
V_k = \sum_{l=1}^{L} \alpha_k l \beta_k l x_{k l},
\]

(7a)

When exploring ALNA, an especially important consideration is the manner in which the
qualitative attribute(s) of interest enter into the utility expression. Expressing the attribute
using dummy-codes would mean that it would not be possible to disentangle whether the
model is uncovering ALNA behaviour or preference heterogeneity (i.e., different marginal
changes from the attribute level that is dropped by the utility expression). Alternatively, one
could use effects-coding, but this would also lead to identification issues between ALNA and
preferences. Our solution is to use dummy-coding to distinguish the attribute’s levels, but to
include all levels in the expression using effects-coding. To avoid perfect multicollinearity, we
arbitrarily express one of the attribute level coefficients as the negative sum of the other level
coefficients (i.e., so that \(\sum_{l=1}^{L} \beta_l = 0\)). In this case, Eq. 7a can be rearranged as follows:

\(^{1}\)These are the variables with no natural sense of ordering.
\begin{equation}
V_k = \sum_{l=1}^{L-1} \alpha^s_{kl} \beta_{kl} x_{kl} - \alpha_{kL} \sum_{l=1}^{L-1} \beta_{kl} x_{kl}. \tag{7b}
\end{equation}

In so doing, we are in a better position to jointly identify the marginal utilities and probabilities of ALNA.\textsuperscript{2} Nevertheless, we are fully aware of the difficulties in separating non-attendance and indifferences in preferences (e.g., see Hess et al., 2013; Hensher, Collins and Greene, 2012, for an overview of the issues).\textsuperscript{3}

### 3. Survey design and data

The empirical data used in the study is based on a choice experiment that was designed to elicit the general public’s preferences for health service innovations in West Yorkshire, UK. Within the DCE, respondents were presented with innovation scenarios, that 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 (see Table 1 for details). Attributes and their associated levels were identified from literature reviews and policy documents (e.g., NICE), interviews with Foundation Trust managers and Trust members, and a focus group discussion with people who live in the area. The survey attributes, the number of choice tasks, and survey question framing were further tested using two pilot surveys.

Various reasons lay behind the final selection of these attributes. Different health issues differentially impact on certain population and age groups, and thus, may result in different

\textsuperscript{2}We fully recognise and appreciate any concerns of identification. In an attempt to explore the issue ourselves, we ran a large number of tests (including simulating a large number of datasets with different parameters). Results from each of these tests confirmed that the correct parameters are retrieved, even under a variety of starting values. On the basis of these tests we are satisfied that the model is identifiable.

\textsuperscript{3}In model estimation, we focus on the simple case where the preferences are homogeneous; however, we note that it could be extended to other underlying models, including random parameters logit to simultaneously account for unobserved preference heterogeneity as well as processing heterogeneity. However, we remark that the additional computational burden of introducing random parameters could make model estimation impractical. While, in this paper, we assume preference homogeneity, we recognise the work by Campbell and Doherty (2013); Hess et al. (2013) where discrete and continuous distributions are accommodated concurrently. We note that this is an interesting area for future exploration.
needs for an innovation between groups (Olsen, 1997), as well as the capacity to benefit (NICE, 2008, p.47). Although ‘target age’ has been a contentious decision criterion for health service prioritisation (e.g., Kappel and Sandøe, 1992; Bowling, 1996; Tsuchiya, 1999), we included it in the study to investigate whether, as is often assumed rather than established, there are systematic differences in the public’s preferences for innovations targeting certain age groups. The length of time needed to implement an innovation is also added to the study to explore whether the public considers time as an important factor and are willing to trade-off potential health benefits for innovations that are implemented sooner. Given that the strength of the evidence underpinning effectiveness is also a determinant of innovation diffusion and adoption (e.g., see Grimshaw et al., 2004; Harris and Mortimer, 2008), we included an attribute to tease out the public's preferences for innovations with different levels of effectiveness. We described the levels of this attribute using an approach similar to Farrar et al. (2000) and Cunningham et al. (2009), with differing levels of certainty and strength. Although the potential health benefit of an innovation is another important drive for its implementation (Edwards et al., 2003; Scott and Lees, 2008; Green and Gerard, 2009), measuring it can be challenging due to the lack of information on who the main beneficiaries are and the extent to which they benefit. Green and Gerard (2009) overcome this using qualitative categories of changes in health (e.g., small, medium, large gains)—an approach in which people may interpret categories differently. Quantitative measures are, alternatively, used in measuring changes in health (e.g., Scott and Lees, 2008; Bryan et al., 2002). However, the lack of reliable data, difficulty in generalising to future applications, and difficulty explaining quantitative measures to the general public often pose as a considerable barrier to widespread use. To overcome this, we quantified potential changes in health status using a multi-attribute health status classification system, EQ-5D\(^4\) (EuroQol Group, 2007) and presented it via a visual ‘health status scale’, ranging from 0 to 100. This scale presents ‘common core’ health states identified by EuroQol Group (2007, p.31): worst health (score 0), moderate health (score 50), good health (score 75), and best health (score 100). As for the cost attribute, we calculated the

\(^4\)EQ-5D has five dimensions; mobility, self-care, usual activities, pain/discomfort, and anxiety/depression. Each dimension has three levels; no problem, some problems, and extreme problems, resulting in 243 ‘scored’ health states. For more details on scoring, please see (EuroQol Group, 2007)
mean annual healthcare expenditure per person in the UK in 2012 at around £2,400 using Office of Health Economics (OHE) statistics. Extra money for innovation implementation was assumed to be increments of this expenditure per person in a month: 5% (£10), 10% (£20), 15% (£30), and 20% (£40). Pilot surveys and interviews with health professionals confirmed these levels as appropriate.

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.

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 2001 UK census data suggests that people in our sample were similar to 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

4.1. Estimation Results

Table 2 presents estimation results from the three models: (1) a standard MNL model; (2) a discrete mixture model accommodating ANA; and, (3) a discrete mixture model accommodating both ANA (for five attributes) and ALNA (for the six qualitative levels of the ‘target population’ attribute). For the three models, all levels of the variables are included with the constraint
that $\sum L = 0$. To facilitate interpretation, we report marginal utilities for all levels and their associated $t$-ratios. We note, though, that the number of parameters and the information criteria measures reported in Table 2 account for these constraints.

Under the MNL model, it is assumed that all attributes are fully considered. According to the results, 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, $(ASC)$, also effects-coded, for the ‘none’ option is also negative and significant, implying that respondents, all else being equal, prefer the implementation of innovation options. In general, respondents prefer options that; (1) are proven scientifically; (2) have more than a ‘moderate’ health gain; (3) take less than six months to implement; and, (4) target the young and adults. Respondents also prefer investment in innovations that target people with ‘cancer’, ‘disability’, ‘mental health problems’, and ‘asthma’, but dislike innovations that target people with ‘drug addiction’ and ‘obesity’.

Because it might be unrealistic to assume that all respondents considered all attributes while making their choices, we move to a second model, which is aimed at accommodating ANA behaviour. In this case, we include discrete variables for all six attributes (i.e., target age, time to implement, evidence on effectiveness, health gain, cost, and target population), resulting in $S = 2^6 = 64$ possible combinations. As can be seen from a comparison of the log-likelihood values, moving from the basic MNL model to the ANA model improves the model fit dramatically (by over 500 log-likelihood units at the expense of six more additional parameters). We also draw attention to the existence of ANA among respondents with significant values of $\pi_k^0$. The fact that $\pi_k^0$ is found to be significant for all attributes is important, since it indicates that for all attributes a subset of respondents did not attend to them. While the most ignored attribute is the ‘implementation time’ (89 percent), the least ignored attribute is ‘target population’ (34 percent). We also observe that 85 percent of the respondents ignore the ‘cost’ attribute. Although this is of concern for WTP estimations, we remark that it is within
the range observed in other studies (for example Scarpa et al. (2009) found over 90 percent non-attendance to cost, Campbell et al. (2011) found 60 percent, and Hole (2011a) found 75 percent). The non-attendance to cost in our context might be, *inter alia*, due to the difficulty in conceptualising ‘innovations’ and the difficulty in trading-off attributes with the cost. Another reason might be that respondents may not think (or have difficulty in understanding) that they will have to pay for the innovations through their tax contributions. Similar to the MNL results, in the ANA model, 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. Although, it should be recognised that these preferences represent only the subset of respondents who considered the attribute.

These findings also hold in the third model, which introduces a further element to the accommodation of non-attendance. This third model considers non-attendance for five attributes and the six levels of the ‘target population’, yielding \( S = 2^{11} = 2,048 \) combinations. In this combined ANA and ALNA model, the direction of preferences and the probabilities of ignoring attributes are quite similar to those in ANA model. With a particular focus on ‘target population’, in the ANA model, we observe that the non-attendance to ‘target population’ is around 34 percent, regardless of the type of target group. However, in the ALNA model, we see that the incidence of non-attendance differs across target groups: in fact, it ranges between 25 percent and 81 percent. Specifically, while respondents ignore the level relating to the people with ‘obesity’ the most (81%), more than three-quarters are predicted to have considered the level associated with ‘cancer patients’ when making choices between innovation investment options. This clearly shows that the typical assumption within ANA studies, where non-attendance applies equally to all levels of an attribute, is incorrect in this application. This result supports the idea that respondents actually only ignore specific levels of an attribute and not necessarily the attribute per se. This is further reinforced by the fact that the combined ANA and ALNA model is associated with a superior model fit. In fact, at the expense of five additional parameters the log-likelihood increases by over 200 units compared to the model where non-attendance is judged to apply to the entire attribute. Importantly, the
three information criteria measures confirm this finding even after accounting for the loss of parsimony.

4.2. Willingness-to-pay (WTP) Estimates

Table 3 compares the marginal WTP results derived under the three models, using the ratios \(-\hat{\beta}_k/\hat{\beta}_{cost}\). As can be seen, and as already deduced from the results in Table 2, irrespective of the model assumptions respondents are willing to pay most for innovations that are scientifically proven, have at least moderate health benefit, take less time to implement, and target adults and the young. With a particular focus on ‘target populations’, under all models, all else being equal, relative to people with a ‘mental health problem’, respondents dislike spending on people with ‘obesity’, ‘drug addiction’, and ‘asthma’ the most, and are willing to pay most for innovations targeting ‘cancer patients’.

[Table 3 about here.]

Of central relevance in this paper is the general significant reduction in marginal WTP estimates (in absolute terms) as one moves from the MNL model to the models that account for processing strategies. However, we point out that the marginal WTP estimates reported for the ANA and the combined ANA and ALNA models apply only to the subset of respondents who actually considered the cost attribute and the relevant attribute/attribute-level (as well as the baseline level in the ANA-ALNA). This issue aside, we note that the confidence intervals are generally much tighter in both non-attendance models than the MNL model, which would imply that the marginal WTP estimates for the subset of the respondents who attended to the attributes are more precisely estimated than the marginal WTP estimates for the sample as a whole. A comparison of the marginal WTP values (relative to their respective baseline levels) retrieved under the ANA and the combined ANA and ALNA models reveals significant differences only for the target population attribute. In particular, significant differences are found in the marginal WTP estimates obtained for people with disability \(t_{(593,0.05)} = 3.26\), drug addiction \(t_{(593,0.05)} = 6.41\), and obesity \(t_{(593,0.05)} = 5.73\).
5. Conclusions

A growing number of papers in the discrete choice experiment (DCE) literature have highlighted the phenomenon of respondents adopting different information processing strategies, including attribute non-attendance (ANA). The findings from this research have cast doubt on the assumption that all respondents consider the full set of alternative attributes. In this paper, we extend this line of enquiry by uncovering non-attendance to attribute-levels. While respondents may attend to an attribute, they may ignore a subset of its levels. In such cases, assuming the same level of attendance to the attribute-levels (i.e., ANA) is erroneous and could have implications when drawing policy recommendations. Additionally, it is especially important to investigate non-attendance when the levels of an attribute are distinct and qualitative, which is common in health related DCEs. In this research, we present an approach to uncover attribute-level non-attendance (ALNA) for the attribute ‘target population’ that consists of six distinct, qualitative levels: people with (1) disability, (2) obesity, (3) cancer, (4) drug addiction, (5) asthma, and (6) mental health problems. In the context of prioritisation of health service innovations, assuming that all respondents consider (or ignore) these groups of target people the same way may not be realistic, due to various reasons, such as, genuine disinterest, different motivations in the choice of innovations, or complexity of tasks due to a large number of levels included in the experiment. It is, therefore, not surprising to observe that some respondents ignore innovations targeting people with ‘obesity’, but consider ‘cancer patients’ when making choices. Health policies based on analyses that do not acknowledge such situations may be misleading.

The modelling approach used in this paper accommodates non-attendance to both attributes and attribute-levels using discrete mixture logit (DML) models. In practice, the DML approach is formally equivalent to latent class logit models, with the main difference being that probabilities of (non)attendance are estimated for each attribute coefficient independently, rather than for combinations of coefficients. Our first model aimed at accommodating non-attendance is based on the standard assumption hitherto of ANA. The results of this model provide further empirical evidence that a subset of respondents do not make trade-offs
between some of the attributes. Our final model attempted to account for a more realistic processing strategy. In this case, we allowed for non-attendance to five attributes and non-attendance to the six levels of the 'target population' attribute. The results from this analysis show that: (1) the respondents consider health service innovation attributes to a different extent; (2) the respondents consider innovations targeting different population groups differently; and, (3) accounting for ANA and ALNA substantially improves the model fit.

The overall results provide further confirmation of the need for accommodating ANA in health DCEs. With the exception of the current paper, only a few studies have extended the analysis of non-attendance to the levels of attributes (e.g., Campbell et al., 2012). Our findings suggest that this is an important issue that needs to be addressed, especially when attribute-levels are distinct and qualitative. From a policy perspective, our study provides policy-makers with the public's valuation of (and acceptability of) various healthcare innovation scenarios. We do this by trading-off clear and explicit criteria rather than opaque criteria or procedures (Hope, 2001; Birch and Gafni, 2002). The methods and findings illuminate public preferences in ways that are rich enough to be useful to policy makers and ultimately make the process of deciding 'who gets what' ever more visible and thus open to questions and challenges.

Although this paper highlights the importance of and need for identifying non-attendance at the level of attribute-levels, there are some limitations which are left for future research. To avoid confounding low sensitivity to an attribute with non-attendance future studies should identify and deal with heterogeneity in preferences as well as in processing strategies (e.g., Hess et al., 2013; Hess and Hensher, 2013). Also, while our study assumes that the choice tasks are equally complex, some tasks may be perceived to be more complex than others by the respondents, and in such cases it may be necessary to examine non-attendance at the choice task level. Finally, the welfare estimates derived in this study are based on a small subset of respondents, due to the high rate of non-attendance to the 'cost' attribute. Although this has been also an issue in some other studies (e.g., Scarpa et al., 2009; Campbell et al., 2011; Hole, 2011a), interpretation of the welfare estimates requires caution.
Acknowledgements

To be included.

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<table>
<thead>
<tr>
<th>Attribute (codes)</th>
<th>Levels (codes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Target population (targetp)</td>
<td>People with disability (targetp_{disabled})</td>
</tr>
<tr>
<td></td>
<td>People with cancer (targetp_{cancer})</td>
</tr>
<tr>
<td></td>
<td>People with mental health problems (targetp_{mental})</td>
</tr>
<tr>
<td></td>
<td>People with obesity (targetp_{obese})</td>
</tr>
<tr>
<td></td>
<td>People with asthma (targetp_{asthma})</td>
</tr>
<tr>
<td></td>
<td>People with drug addictions (targetp_{drug})</td>
</tr>
<tr>
<td>Age group (targeta)</td>
<td>Young (less than 18) (targeta_{young})</td>
</tr>
<tr>
<td></td>
<td>Adults (18-65) (targeta_{adult})</td>
</tr>
<tr>
<td></td>
<td>Elderly (more than 65) (targeta_{elderly})</td>
</tr>
<tr>
<td>Time to get into practice (imptime)</td>
<td>0-5 months (imptime_{0-5})</td>
</tr>
<tr>
<td></td>
<td>6-12 months (imptime_{6-12})</td>
</tr>
<tr>
<td></td>
<td>More than 12 months (imptime_{12})</td>
</tr>
<tr>
<td>Whether it works (eveff)</td>
<td>It works and scientific studies confirm this (eveff_{sci})</td>
</tr>
<tr>
<td></td>
<td>It works but not scientifically proven (eveff_{nosci})</td>
</tr>
<tr>
<td></td>
<td>Experts say it works elsewhere in the NHS (eveff_{expert})</td>
</tr>
<tr>
<td>Potential health benefit/gain (healthg)</td>
<td>Best health (100%) (healthg_{100})</td>
</tr>
<tr>
<td></td>
<td>Good health (75%) (healthg_{75})</td>
</tr>
<tr>
<td></td>
<td>Moderate health (50%) (healthg_{50})</td>
</tr>
<tr>
<td>Cost to you as a taxpayer (£/month) (cost)</td>
<td>10, 20, 30, and 40</td>
</tr>
</tbody>
</table>
### Table 2. Estimation results

<table>
<thead>
<tr>
<th>Name</th>
<th>MNL</th>
<th>ANA&lt;sup&gt;a&lt;/sup&gt;</th>
<th>ANA&amp;ALNA&lt;sup&gt;a&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>t-ratio</td>
<td>Estimate</td>
</tr>
<tr>
<td>$\hat{\beta}_{ASC}$</td>
<td>-0.781</td>
<td>-29.22</td>
<td>-0.932</td>
</tr>
<tr>
<td>$\hat{\beta}_{cost}$</td>
<td>-0.011</td>
<td>-8.17</td>
<td>-0.106</td>
</tr>
<tr>
<td>$\hat{\beta}<em>{eveff</em>{noci}}$</td>
<td>-0.231</td>
<td>-9.28</td>
<td>-0.789</td>
</tr>
<tr>
<td>$\hat{\beta}<em>{eveff</em>{sci}}$</td>
<td>0.176</td>
<td>7.90</td>
<td>0.669</td>
</tr>
<tr>
<td>$\hat{\beta}<em>{eveff</em>{expert}}$</td>
<td>0.056</td>
<td>2.42</td>
<td>0.121</td>
</tr>
<tr>
<td>$\hat{\beta}<em>{healthg</em>{50}}$</td>
<td>-0.301</td>
<td>-12.08</td>
<td>-0.787</td>
</tr>
<tr>
<td>$\hat{\beta}<em>{healthg</em>{75}}$</td>
<td>0.090</td>
<td>4.05</td>
<td>0.177</td>
</tr>
<tr>
<td>$\hat{\beta}<em>{healthg</em>{100}}$</td>
<td>0.176</td>
<td>7.90</td>
<td>0.669</td>
</tr>
<tr>
<td>$\hat{\beta}<em>{imptime</em>{6-12}}$</td>
<td>-0.012</td>
<td>-0.52</td>
<td>-0.370</td>
</tr>
<tr>
<td>$\hat{\beta}<em>{imptime</em>{12}}$</td>
<td>-0.056</td>
<td>-2.49</td>
<td>-0.484</td>
</tr>
<tr>
<td>$\hat{\beta}<em>{imptime</em>{0-5}}$</td>
<td>0.068</td>
<td>3.08</td>
<td>0.854</td>
</tr>
<tr>
<td>$\hat{\beta}<em>{target</em>{a_{young}}}$</td>
<td>0.097</td>
<td>4.05</td>
<td>0.646</td>
</tr>
<tr>
<td>$\hat{\beta}<em>{target</em>{a_{elderly}}}$</td>
<td>-0.254</td>
<td>-10.86</td>
<td>-1.420</td>
</tr>
<tr>
<td>$\hat{\beta}<em>{target</em>{a_{adult}}}$</td>
<td>0.157</td>
<td>6.36</td>
<td>0.776</td>
</tr>
<tr>
<td>$\hat{\beta}<em>{target</em>{p_{disabled}}}$</td>
<td>0.466</td>
<td>11.03</td>
<td>0.951</td>
</tr>
<tr>
<td>$\hat{\beta}<em>{target</em>{p_{cancer}}}$</td>
<td>1.380</td>
<td>16.67</td>
<td>2.630</td>
</tr>
<tr>
<td>$\hat{\beta}<em>{target</em>{p_{mental}}}$</td>
<td>0.327</td>
<td>5.46</td>
<td>0.854</td>
</tr>
<tr>
<td>$\hat{\beta}<em>{target</em>{p_{obese}}}$</td>
<td>-0.955</td>
<td>-19.43</td>
<td>-1.740</td>
</tr>
<tr>
<td>$\hat{\beta}<em>{target</em>{p_{asthma}}}$</td>
<td>0.133</td>
<td>2.32</td>
<td>0.276</td>
</tr>
<tr>
<td>$\hat{\pi}<em>0</em>{target_{a_{young}}}$</td>
<td>0.665</td>
<td>20.02</td>
<td>0.656</td>
</tr>
<tr>
<td>$\hat{\pi}<em>0</em>{cost}$</td>
<td>0.852</td>
<td>45.34</td>
<td>0.853</td>
</tr>
<tr>
<td>$\hat{\pi}<em>0</em>{eveff}$</td>
<td>0.691</td>
<td>9.85</td>
<td>0.643</td>
</tr>
<tr>
<td>$\hat{\pi}<em>0</em>{healthg_{50}}$</td>
<td>0.552</td>
<td>9.43</td>
<td>0.492</td>
</tr>
<tr>
<td>$\hat{\pi}<em>0</em>{imptime}$</td>
<td>0.890</td>
<td>14.11</td>
<td>0.857</td>
</tr>
<tr>
<td>$\hat{\pi}<em>0</em>{target_{p_{disabled}}}$</td>
<td>0.341</td>
<td>10.64</td>
<td>0.332</td>
</tr>
<tr>
<td>$\hat{\pi}<em>0</em>{target_{p_{drug}}}$</td>
<td>0.664</td>
<td>24.83</td>
<td>0.664</td>
</tr>
<tr>
<td>$\hat{\pi}<em>0</em>{target_{p_{cancer}}}$</td>
<td>0.247</td>
<td>7.29</td>
<td>0.247</td>
</tr>
<tr>
<td>$\hat{\pi}<em>0</em>{target_{p_{mental}}}$</td>
<td>0.561</td>
<td>9.02</td>
<td>0.561</td>
</tr>
<tr>
<td>$\hat{\pi}<em>0</em>{target_{p_{obese}}}$</td>
<td>0.812</td>
<td>39.79</td>
<td>0.812</td>
</tr>
<tr>
<td>$\hat{\pi}<em>0</em>{target_{p_{asthma}}}$</td>
<td>0.484</td>
<td>7.26</td>
<td>0.484</td>
</tr>
</tbody>
</table>

| $LL(\hat{\beta})$ | -6,390.409 | -5,855.634 | -5,631.201 |
| $\rho^2$ | 0.184 | 0.252 | 0.281 |
| AIC | 12,810.818 | 11,753.268 | 11,314.402 |
| BIC | 12,876.621 | 11,845.393 | 11,428.461 |
| CAIC | 12,788.208 | 11,718.658 | 11,269.792 |
| $N$(param.) | 15 | 21 | 26 |
| $N$(obs.) | 7,128 | 7,128 | 7,128 |

<sup>a</sup> Since $\pi^0 + \pi^1 = 1$, for the sake of brevity we report only $\pi^0$. 
### Table 3. Marginal WTP estimates (£/month)

<table>
<thead>
<tr>
<th></th>
<th>MNL</th>
<th>ANA</th>
<th>ANA&amp;ALNA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Value</td>
<td>CI[95%]</td>
<td>Value</td>
</tr>
<tr>
<td>$\hat{WTP}_{eff,sci}$</td>
<td>-10.91</td>
<td>[-18.06 , -3.76]</td>
<td>-5.17</td>
</tr>
<tr>
<td>$\hat{WTP}<em>{healthg}$</em>{5}</td>
<td>35.55</td>
<td>[23.91 , 47.18]</td>
<td>9.09</td>
</tr>
<tr>
<td>$\hat{WTP}<em>{healthg}$</em>{100}</td>
<td>46.55</td>
<td>[33.03 , 60.06]</td>
<td>13.18</td>
</tr>
<tr>
<td>$\hat{WTP}<em>{imptime}$</em>{6−12}</td>
<td>-7.27</td>
<td>[-14.31 , -0.23]</td>
<td>-11.55</td>
</tr>
<tr>
<td>$\hat{WTP}<em>{imptime}$</em>{12}</td>
<td>-11.27</td>
<td>[-18.60 , -3.95]</td>
<td>-12.62</td>
</tr>
<tr>
<td>$\hat{WTP}_{targeta,elderly}$</td>
<td>12.64</td>
<td>[-2.37 , 27.64]</td>
<td>5.29</td>
</tr>
<tr>
<td>$\hat{WTP}_{targeta,disabled}$</td>
<td>-152.45</td>
<td>[-190.04 , -114.87]</td>
<td>-27.36</td>
</tr>
<tr>
<td>$\hat{WTP}_{targeta,obese}$</td>
<td>-116.55</td>
<td>[-146.82 , -86.27]</td>
<td>-20.09</td>
</tr>
<tr>
<td>$\hat{WTP}_{targeta,asthma}$</td>
<td>-17.64</td>
<td>[-33.17 , -2.10]</td>
<td>-1.08</td>
</tr>
<tr>
<td>$\hat{WTP}_{ASC}$</td>
<td>142.00</td>
<td>[113.24 , 170.76]</td>
<td>17.58</td>
</tr>
</tbody>
</table>

*a* Represents 95% confidence intervals, obtained using the Delta method.
Which one of the following innovations would you prefer your local NHS to spend its budget on?

<table>
<thead>
<tr>
<th>People:</th>
<th>Option 1</th>
<th>Option 2</th>
<th>Option 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age group:</td>
<td>Disabled people</td>
<td>Obese people</td>
<td>None of them</td>
</tr>
<tr>
<td>Time to get into the NHS:</td>
<td>Elderly (more than 65)</td>
<td>Young (less than 10)</td>
<td></td>
</tr>
<tr>
<td>Whether it works:</td>
<td>Experts say it works elsewhere in the NHS</td>
<td>It works and scientific studies confirm this</td>
<td></td>
</tr>
<tr>
<td>Potential health gain:</td>
<td>Good Health</td>
<td>Moderate Health</td>
<td></td>
</tr>
<tr>
<td>Cost to you (£/month):</td>
<td>£40</td>
<td>£10</td>
<td></td>
</tr>
</tbody>
</table>

Tick the ONE you prefer the MOST

---

**Figure 1.** A sample DCE task