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INVESTIGATING ATTRIBUTE NON-ATTENDANCE AND ITS CONSEQUENCES IN CHOICE EXPERIMENTS WITH LATENT CLASS MODELS

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ABSTRACT

A growing literature, mainly from transport and environment economics, has started to explore whether respondents violate some of the axioms about individuals' preferences in Discrete Choice Experiments (DCEs) and use simple strategies to make their choices. One of these strategies, termed attribute non-attendance (ANA), consists in ignoring one or more attributes. Using data from a DCE administered to healthcare providers in Ghana to evaluate their potential resistance to changes in clinical guidelines, this study illustrates how latent class models can be used in a step-wise approach to account for all possible ANA strategies used by respondents and explore the consequences of such behaviours. Results show that less than 3% of respondents considered all attributes when choosing between the two hypothetical scenarios proposed, with a majority looking at only one or two attributes. Accounting for ANA strategies improved the goodness-of-fit of the model and affected the magnitude of some of the coefficient and willingness-to-pay estimates. However, there was no difference in the predicted probabilities of the model taking into account ANA and the standard approach. Although the latter result is reassuring about the ability of DCEs to produce unbiased policy guidance, it should be confirmed by other studies.

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KEY WORDS: discrete choice experiments; decision heuristics; latent-class models

1. INTRODUCTION

At a time when publicly provided healthcare systems have limited resources to address an ever-growing demand, critical decisions have to be made to allocate scarce resources efficiently. Among the techniques used by health economists to inform such decisions, discrete choice experiments (DCEs) have emerged as a key tool to value the preferences of health service users and providers over a number of alternative attributes. The policy and welfare outputs derived from DCE studies have, in turn, been used in economic analysis models to inform decision making.

The analysis of DCEs is grounded in the economic theory of consumer behaviour (Lancaster, 1966; McFadden, 1974), which posits three axioms about individuals' preferences: that they are complete, monotonic and continuous. Continuity of preferences implies that individuals use compensatory decision-making processes, meaning that they take into account all the available information to make their decisions. Typically, in a DCE, this implies that respondents make trade-offs between all attributes to choose their preferred alternative.

However, psychologists have shown that people often avoid making trade-offs and instead use simple rules, or heuristics, to make their decisions (Payne *et al.*, 1993). In the health economics literature, several studies have tested that axiom in DCE studies. The majority have focused on detecting a particular form of

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respondents' discontinuous preferences: the existence of dominant preferences. This is performed by identifying those respondents who hold non-compensatory preferences for a given attribute and, therefore, systematically choose the scenario with the best level for that attribute (Bryan *et al.*, 1998; Ryan *et al.*, 2000; McIntosh and Ryan, 2002; Scott, 2002). Most of these studies have found that a large proportion of respondents have indeed dominant preferences. However, this evidence of preference discontinuity is limited in several ways. First, the approach taken in these studies may not always be comprehensive. Indeed, given the choice sets created by a fractional factorial design, a simple observation of response patterns may not enable the distinction between respondents who are willing to make trade-offs and those who are not. Second, the identification of dominant preferences only provides a partial vision of respondents' preference discontinuity. Respondents might be identified as 'traders' as long as they have compensatory preferences over a sub-set of attributes, although, in fact, they might be ignoring the rest of the attributes proposed, hence not trading among all attributes. Finally, as underlined in a recent qualitative study of respondents' heuristics (Ryan *et al.*, 2009), the approach used in these studies does not resolve the question of how to incorporate such discontinuous preferences in the analysis.

Researchers in environment and transport economics have recently used quantitative methods to identify and account for attribute processing strategies whereby respondents use particular rules to make their decisions more easily. One of these strategies, termed attribute non-attendance (ANA), is a direct violation of the assumption of continuity of preferences because it consists in ignoring the information contained in one or more attributes (Hensher *et al.*, 2005; Hess and Rose, 2007; Campbell *et al.*, 2008; Hensher and Rose, 2009; Scarpa *et al.*, 2009; Hensher and Greene, 2010). By definition, individuals who have dominant preferences will ignore the information contained in all but one attribute. Therefore, the identification of ANA subsumes the analysis of dominant preferences traditionally undertaken in health economics and provides a more comprehensive quantitative alternative to the study of this problem.

Identifying ANA in health DCEs is important for several reasons. First, ignoring attributes means that individuals have a non-compensatory behaviour: if one attribute is ignored, any improvement in this attribute will fail to compensate individuals for a reduction in utility through another attribute level. Consequently, there is a violation of the continuity axiom, which implies that preferences should not be represented by conventional utility functions (Lancsar and Louviere, 2006). Second, ignoring ANA strategies could lead to biased coefficients and, therefore, biased welfare and policy outputs. Finally, DCEs in health could be particularly prone to the use of attribute processing strategies: when choice experiments include a strong attribute, such as health outcomes, respondents might be more likely to focus on this one at the expense of others.

Two different approaches have been used to study attribute non-attendance: Stated and inferred non-attendance (INA) approach (Mariel *et al.*, 2011). The stated approach consists in basing the analysis on complementary information retrieved from respondents who state the ANA rules they employed. Several studies have questioned the extent to which one could trust respondents' declarations (Campbell and Lorimer, 2009), particularly as they sometimes state to have ignored an attribute, although, in fact, they only gave it less weight (Carlsson *et al.*, 2010; Hess and Hensher, 2010). In contrast, the INA approach uses analytical models to infer the rules used by respondents. This approach typically relies on latent class models (LCMs), where each class represents a certain non-attendance decision rule, where the attributes ignored have a parameter set to zero (Hess and Rose, 2007; Scarpa *et al.*, 2009; Campbell *et al.*, 2010; Hensher and Greene, 2010).

This paper proposes a step-wise approach with latent class models to investigate the different ANA patterns used by healthcare providers completing a DCE in Ghana and to explore the consequences of such heuristics on welfare and policy outputs.

This paper first contributes to the growing quantitative literature analysing whether individuals have ignored one or more attributes. One of the limitations of the INA approach is that it can often only include a subset of attribute permutations, as the number of classes grows exponentially with the number of attributes (Hole, 2011a). Indeed, a '2^k model' that simultaneously tests all ANA combinations is often impossible to estimate because of sample restrictions and has only been evaluated in one DCE where the five attributes led to 32 ANA rules (Campbell *et al.*, 2010). Here, a simple step-wise approach is proposed that allows the analyst to overcome this problem in the case of a larger DCE (six attributes) administered to a smaller sample. In a nutshell, the strategy

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consists in estimating a successive number of LCMs where classes representing particular ANA combinations are only kept in subsequent specifications if their class probability is not zero.

Second, this article contributes to the study of heuristics in DCEs in the health literature. As underlined before, the majority of DCE studies in health have identified dominant preferences, which constitute special cases of ANA. This paper not only describes and accounts for dominant preferences, but it encompasses all other ANA response strategies. Doing that, it adds to a very limited literature in health, where ANA has been mostly ignored despite its critical importance and potential relevance. One qualitative study of the responses given by 18 respondents in a DCE exploring preferences for cancer screening identified that only five respondents seemed to consider all attributes, whereas the rest revealed that they employed various attribute non-attendance strategies (Ryan *et al*., 2009). In a recent study, Hole (2011b) used a two-step process to account for endogenous ANA of respondents and found that '*a substantial share of the respondents ignored one or more attributes when making their choices*'. Although his approach overcame the problems of LCMs mentioned above, it did not present a precise description of the various ANA rules employed by respondents. In contrast with Hole (2011b), which is, to date, the unique quantitative study of ANA in health DCEs, this paper provides a full description of all the response patterns used by respondents in the DCE, as well as their frequency.

Finally, this paper adds to the studies testing the impact of ignoring ANA on DCE outputs. Most of this literature has shown that ignoring ANA can yield to biased willingness-to-pay estimates (Scarpa *et al*., 2009; Carlsson *et al*., 2010; Hensher, 2010; Hole, 2011b). To our knowledge, no study has investigated the impact of ANA on another DCE output sometimes useful for policymakers: demand forecasting, although the modelling of policy or programme uptake probabilities. In this study, both DCE outputs are computed, one compares the extent of the differences observed when accounting for ANA or not.

The article is organised as follows. Section 2 outlines the methodological approach. Section 3 briefly presents the survey and data used in the analysis. Section 4 presents the results. Finally, section 5 discusses the findings and provides a number of conclusions.

2. METHODS

2.1. Using latent class models to account for attribute non-attendance

Through their econometric specification, LCMs provide an alternative approach to models such as multinomial logit and mixed logit to accommodate response heterogeneity. In LCMs, it is assumed that the population of respondents can be divided into a set number (Q) of classes, or groups of individuals, who will differ in their preferences. In other words, although the groups are different from each other (i.e. they are defined by different parameter vectors), all members of a same group share the same parameters. As the analyst ignores which observation is in which class, the model assumes that individuals belong to a certain group up to a probability. The logit choice probability function of choosing one particular alternative from J alternatives for an individual i belonging to a specific class q can be then written as

$$Pr\ (\mathrm{y}_{\mathrm{it}} = 1\ |class\ q) = \ \mathrm{P}_{it|}\mathrm{q} = \frac{e^{X_{itj}^{'}\beta_q}}{\sum_{\mathbf{j}=1}^{J} e^{X_{itj}^{'}\beta_q}} \tag{1}$$

The probability that an individual i belongs to class q (out of a total of Q classes) is given by

$$H_{iq} = \frac{e^{\theta_q}}{\sum_{\mathbf{q}=1}^{Q} e^{\theta_q}}, \mathrm{q} = 1, \ldots,\ \mathrm{Q\ and}\ \theta_{\mathrm{Q}} = 0 \tag{2}$$

The Q^{th} parameter vector is normalised to zero to secure identification of the model (Greene and Hensher, 2003). The log-likelihood function to be maximised is therefore the sum over individuals of the log of the expectation over classes of the joint probability of the sequence of T choices:

$$\ln L = \sum\nolimits_{\mathrm{i}=1}^{\mathrm{N}} \ln P_i = \sum\nolimits_{\mathrm{i}=1}^{\mathrm{N}} \ln \sum\nolimits_{\mathrm{q}=1}^{\mathrm{Q}} H_{iq} \prod\nolimits_{t=1}^{T} \mathrm{P}_{it|\mathrm{q}} \tag{3}$$

Having retrieved the parameter estimates, Bayes' formula can be applied to calculate the posterior estimates of the individual-specific class probabilities ($\hat{H}_{q|i}$) conditional on the observed sequence of T choices (Greene and Hensher, 2003):

$$\hat{H}_{q|}i = \frac{\hat{\mathrm{P}}_{i|}\mathrm{q}\hat{H}_{iq}}{\sum_{\mathbf{q}=1}^{Q} \hat{P}_{i|\mathrm{q}\hat{H}_{iq}}} \tag{4}$$

Although each class q can be defined by a vector β_q—see (1)—the analyst can decide to impose particular constraints on these parameters. In the present case, the objective is to test whether respondents have chosen to ignore certain attributes, which is equivalent to setting the coefficient(s) associated with (a) particular attribute(s) to zero (Hess and Rose, 2007; Hensher and Greene, 2010).

2.2. Analytical strategy

The first step of the analysis maps out the extent to which attribute non-attendance is an issue in the dataset. This is carried out by estimating six consecutive two-class LCMs where respondents are either assumed to have considered all attributes (class 1) or to have ignored one attribute (class 2). Following Scarpa *et al*. (2009) and Hensher and Greene (2010), the estimated parameters across the two classes are constrained to be equal to each other. This equality-constrained specification allows the estimation of a model where preferences across individuals can only differ in the information processing rule they use. For these six models, Equation (4) is used to retrieve the distribution of posterior individual probabilities that respondents belong to class 2, that is, ignore one attribute.

Then, a series of LCMs is estimated that aim to capture all ANA strategies that could have been adopted by respondents. In a DCE with k attributes, there are 2^{k} possible permutations of ANA strategies. Here, with six attributes, 64 classes would need to be estimated. Because class membership is defined at the individual level, one might end up with too few individuals in each class with a sample size of 132 individuals. To overcome this problem but still try to identify all ANA patterns used by respondents, a stepwise approach is proposed. Having identified all 64 possible response patterns in the present experiment, the first specification includes eight classes: one class that allows respondents to have not ignored any attribute (class 1), and seven others where only one attribute at a time can be ignored (classes 2–7). As in the previous step, all parameters are constrained to be equal to each other across all classes, forcing the analysis to focus only on ANA patterns. Based on the results of this first model, another LCM is estimated, which includes two types of classes: 'old' and 'new' ones. Old classes are those that were found relevant in the first model (i.e. classes that did not have a class probability equal to zero), whereas those that were not found relevant are dropped. 'New' classes define new ANA patterns, not tested in the previous model estimated. The estimation strategy proceeds as such until all ANA patterns have been included, and the final model includes classes that encompass all the response heuristics used by respondents. In essence, this stepwise strategy logically assumes that if a simple response pattern (e.g. ignoring 'workload') is found irrelevant at an early stage, there is no reason for it to be relevant once more complex response strategies (e.g. ignoring 'workload' and 'anaemia') or unrelated ones (e.g. ignoring 'anaemia' and 'drugs') are introduced.

Finally, the last step tests whether accounting for ANA strategies has an impact on two types of outputs in the DCE. Using the coefficient estimates obtained in the standard logit model and the final ANA model, the following outputs are computed and contrasted: the willingness-to-pay for different aspects of malaria management, and the proportion of respondents who would favour the implementation of a new set of clinical guidelines against the ones currently used.

All models were estimated using a modified version of Nlogit 4.0.

3. DATA

The data used in this study come from a DCE designed to elicit preferences regarding the introduction of new guidelines to managing malaria in pregnancy in Ghana (Lagarde *et al*., 2011). The choice experiment was designed after a series of focus group discussions and in-depth interviews with healthcare providers and a pilot study.

Six attributes describing the conditions of malaria case management by ante-natal care were used (see Table I): the type of treatment approach to managing malaria in pregnancy, the drugs prescribed to pregnant women, the workload, the potential monthly bonus included in the policy and the likely health outcomes for mothers (incidence of severe anaemia) and babies (incidence of low birth weight). An orthogonal D-efficient experimental design of 16 choice sets was created using the macros developed for SAS (Kuhfeld, 2009). Each choice set consisted of two generic alternatives representing two policies that could be introduced to manage malaria in pregnancy (see Figure 1).

In the analysis of DCE responses, the standard random utility framework (McFadden, 1974) is applied. A respondent's utility for a particular alternative is derived from the observed attributes (X) of that alternative and unobserved factors (ε), which are i.i.d. according to the Extreme Value Type I function. In the present application, the utility associated with a particular set of guidelines *J* can be derived as follows:

$$U_{Ji} = WEIGH_J * \beta_{weigh} + ANEM_J * \beta_{ane} + DRUG_J * \beta_{drug} + BONUS_J * \beta_{bon} + WORK_J * \beta_{work} + TREAT_J * \beta_{treat} + \varepsilon_i$$

Based on the vector of coefficient estimates β_i representing taste intensities, the probability that respondents would prefer a new set of guidelines to manage malaria in pregnancy over the current ones can be simulated by computing the probability associated with the utility derived from the new guidelines.

Having randomly selected 68 facilities in the Ashanti region in Ghana, all the staff in the ANC clinic present on the day of the data collection was interviewed. For more details about the study design, refer to Smith Paintain *et al*. (2011). Because each respondent answered a series of 16 choice sets, a total of 2,128 observations were used for model estimations. Ethical approval for this study was granted by the Committee on Human Research, Publications and Ethics, Kwame Nkrumah University of Science and Technology, School of Medical Sciences, Kumasi, Ghana and by the ethics committee of the London School of Hygiene & Tropical Medicine. Written informed consent was sought from all participants before the start of all interviews.

Table I. Attributes and levels in the choice experiment

Attribute	Levels
The type of approach to managing malaria in pregnancy	▪ Preventive approach ▪ Curative approach (test and treat if parasite positive)
The anti-malarial drugs you have to prescribe to pregnant women	▪ SP (Fansidar) ▪ Artesunate-amodiaquine (AS–AQ)
Prevalence of anaemia for mothers treated with protocol	▪ 1% ▪ 15%
Prevalence of low birth weight among infants of mothers treated with the protocol	▪ 10% ▪ 15%
Staffing level for the ANC clinic	▪ Under-staffed ▪ Adequately staffed
The salary supplement included in the protocol	▪ GH. C10 ▪ GH. C20

Table II. Average proportion of respondents who ignored one attribute

Model	Attribute assumed to have been ignored in the second class	Average class membership (%)
Model 1	Low birth weight ignored	7.99
Model 2	Anaemia ignored	17.24
Model 3	Bonus ignored	21.75
Model 4	Workload ignored	46.92
Model 5	Drug ignored	62.57
Model 6	Treatment ignored	66.76

4. RESULTS

4.1. Preliminary description of attribute non-attendance patterns

Table II reports the class membership probabilities of six two-class LCMs, estimated to explore briefly the extent to which respondents may have ignored some of the attributes. As can be seen in Table II, there is a large heterogeneity of non-attendance patterns across attributes. According to Models 1 and 2, the probability of ignoring low birth weight or anaemia (i.e. belonging to class 2), respectively, is low. Only 8% would have completely ignored neonatal outcomes, whereas 17% would have done so in the case of maternal health outcomes. Next, results of Model 3 show that only 22% of the respondents might have ignored the bonus offered in the different approaches. However, for the other three attributes, a majority of respondents seem to have been inclined to ignore them.

To illustrate further the heterogeneity of decision rules employed by respondents, Figure 2 presents the six histograms representing the distributions of individual class probabilities of belonging to class 2 in each of the six estimated models (i.e. to have ignored a particular attribute). The graphs confirm that for three attributes (anaemia, low birth weight and bonus), decision rules seem relatively homogenous. The distributions of class

	NEW POLICY #1	NEW POLICY #2
The type of approach to managing malaria in pregnancy	Preventive drugs for all	Rapid diagnostic used with all, only give drugs to those who test positive
The anti-malarial drugs you have to prescribe to pregnant women	SP / fansidar	SP / fansidar
What is likely to be the results on anaemia for the mothers	15% of women treated with this protocol will develop severe anaemia	15% of women treated with this protocol will develop severe anaemia
What is likely to be the number of babies with a low weight (< 2.5 kg)	15% of babies will be born with low birth weight	10% of babies will be born with low birth weight
Staffing level for the ANC clinic	Under-staffed	Adequately staffed
The salary supplement included in the policy	A monthly salary supplement Of GH. C10	A monthly salary supplement Of GH. C10
Which policy would you choose?	☐	☐

Figure 1. Example of a choice scenario

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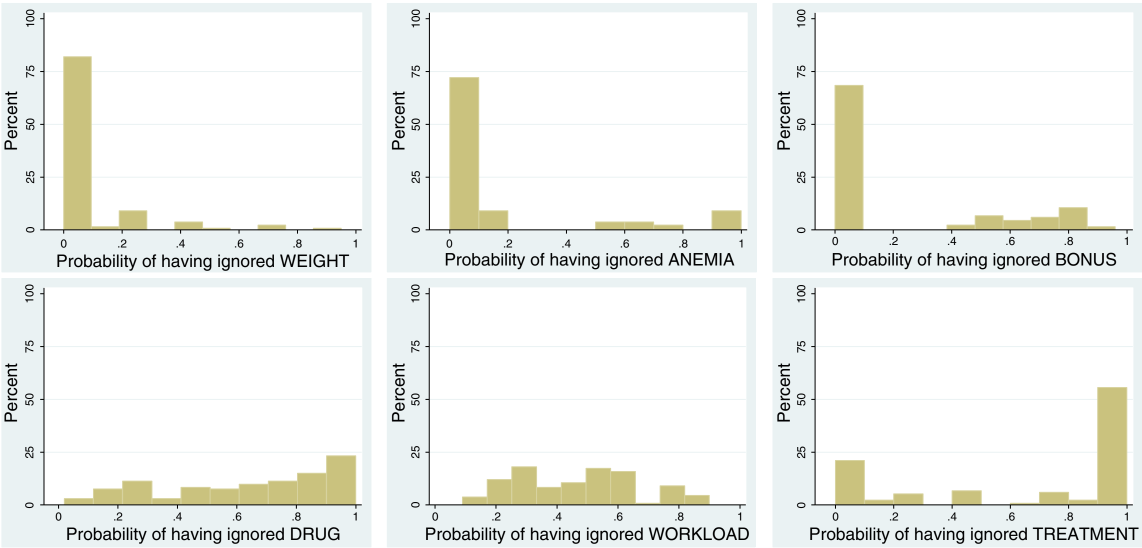

Figure 2. Distribution of individual probabilities of having ignored one attribute (computed separately for six latent class models)

probabilities are clearly right-skewed, showing that very few people were likely to have ignored these attributes. By contrast, the graphical representation of the individual probabilities to have ignored the ‘type of treatment’ attribute (bottom right graph) shows a left-skewed distribution, which confirms that a majority of individuals would ignore the attribute. Finally, the last two histograms (of the probabilities to have ignored the type of drugs and workload) look more like uniform distributions, suggesting more heterogeneity in decision patterns.

4.2. Describing attribute non-attendance patterns

Based on these preliminary descriptive results, eight successive LCMs were estimated to test the simultaneous use of non-attendance strategies by respondents. Table III describes the various response strategies tested in each model, as well as the proportion of respondents who ascribed to each of them.

In model ANA-1, the classes defined assumed that respondents would consider all attributes (class 1) or could only ignore one attribute at a time (class 2–7). Model ANA-2, estimated simultaneously 20 different ANA rules: those that had been found ‘relevant’ in model ANA-1 (all classes except 3 and 4) and the 15 combinations of ignoring two attributes. Most of the 2-level ANA rules were found to be irrelevant, meaning that no respondent seemed to have used most of them (the class probabilities of classes 8–13 and 15–19 were equal to zero). Models ANA-3 and ANA-4 introduce ‘level-3’ ANA rules (ignoring three attributes at the time), models ANA-5 and ANA-6 introduce ‘level-4’ ANA rules (ignoring four attributes at the time) and finally, models ANA-7 and ANA-8 introduce ‘level-5’ ANA rules (ignoring five attributes at the time) and the possibility to ignore all six attributes.

The last column of Table III presents the class probabilities for the final ANA model specification. It shows that the respondents did not use a vast array of ANA strategies in the DCE, with only 10 of the 64 possible response patterns. Overall, it is striking to notice that only 2.6% of respondents (class 1) looked at all attributes. Just less than 20% of them looked at all but the treatment attribute, 25% ignored three attributes (including 20% who followed ‘level-3’ ANA rules that ignored the treatment approach—classes 24 and 32), a further 41.6% of individuals made their decisions based on only two attributes (essentially the two health outcomes, anaemia and low birth weight—see class 43), 7.2% of respondents only looked at the financial bonus attribute and finally, 4.7% ignored all attributes, presumably picking an alternative randomly.

Summing up the probabilities of the latent classes where each of the attributes was ignored, the results indicate that the treatment approach was ignored by 91.2% of respondents. The next less attended attributes were the drug (72.8%) and workload ones (70.0%), whereas the two health outcome attributes, anaemia and

Table III. Details of latent class model specifications and average class membership probabilities

Class no.	Coefficients estimated in the class						Model ANA-1	Model ANA-2	Model ANA-3	Model ANA-4	Model ANA-5	Model ANA-6	Model ANA-7	Model ANA-8	Final ANA Model
1	β_{weigh}	β_{ane}	β_{drug}	β_{bon}	β_{work}	β_{treat}	48.96%	15.01%	1.8%	5.95%	2.33%	1.98%	2.91%	2.58%	2.58%
2	β_{weigh}	β_{ane}	β_{drug}	β_{bon}	β_{work}	0	14.07%	25.75%	38.59%	25.75%	30.74%	28.67%	21.73%	19.58%	19.58%
3	β_{weigh}	β_{ane}	β_{drug}	β_{bon}	0	β_{treat}	0.00%	—	—	—	—	—	—	—	
4	β_{weigh}	β_{ane}	β_{drug}	0	β_{work}	β_{treat}	0.00%	—	—	—	—	—	—	—	
5	β_{weigh}	β_{ane}	0	β_{bon}	β_{work}	β_{treat}	16.70%	4.37%	0.00%	—	—	—	—	—	
6	β_{weigh}	0	β_{drug}	β_{bon}	β_{work}	β_{treat}	16.75%	0.00%	—	—	—	—	—	—	
7	0	β_{ane}	β_{drug}	β_{bon}	β_{work}	β_{treat}	3.52%	0.00%	—	—	—	—	—	—	
	% who ignored one attribute						***51.04%***	***30.12%***	**38.59%**	**25.75%**	**30.74%**	**28.67%**	**21.73%**	**19.58%**	**19.58%**
8	β_{weigh}	β_{ane}	β_{drug}	β_{bon}	0	0	—	0.00%	—	—	—	—	—	—	
9	β_{weigh}	β_{ane}	β_{drug}	0	β_{work}	0	—	0.00%	—	—	—	—	—	—	
10	β_{weigh}	β_{ane}	0	β_{bon}	β_{work}	0	—	0.00%	—	—	—	—	—	—	
11	β_{weigh}	0	β_{drug}	β_{bon}	β_{work}	0	—	0.00%	—	—	—	—	—	—	
12	0	β_{ane}	β_{drug}	β_{bon}	β_{work}	0	—	0.00%	—	—	—	—	—	—	
13	β_{weigh}	β_{ane}	β_{drug}	0	0	β_{treat}	—	0.00%	—	—	—	—	—	—	
14	β_{weigh}	β_{ane}	0	β_{bon}	0	β_{treat}	—	32.3%	0.00%	—	—	—	—	—	
15	β_{weigh}	0	β_{drug}	β_{bon}	0	β_{treat}	—	0.00%	—	—	—	—	—	—	
16	0	β_{ane}	β_{drug}	β_{bon}	0	β_{treat}	—	0.00%	—	—	—	—	—	—	
17	β_{weigh}	β_{ane}	0	0	β_{work}	β_{treat}	—	0.00%	—	—	—	—	—	—	
18	β_{weigh}	0	β_{drug}	0	β_{work}	β_{treat}	—	0.00%	—	—	—	—	—	—	
19	0	β_{ane}	β_{drug}	0	β_{work}	β_{treat}	—	0.00%	—	—	—	—	—	—	
20	β_{weigh}	0	0	β_{bon}	β_{work}	β_{treat}	—	11.09%	2.94	0.00%	—	—	—	—	
21	0	β_{ane}	0	β_{bon}	β_{work}	β_{treat}	—	4.24%	5.31	0.00%	—	—	—	—	
22	0	0	β_{drug}	β_{bon}	β_{work}	β_{treat}	—	7.29%	0.00%	—	—	—	—	—	
	% who ignored two attributes						-	***54.92%***	***8.25%***	***0.00%***	***0.00%***	—	***0.00%***	***0.00%***	***0.00%***
23	β_{weigh}	β_{ane}	β_{drug}	0	0	0	—	—	0.00%	—	—	—	—	—	
24	β_{weigh}	β_{ane}	0	β_{bon}	0	0	—	—	29.38%	23.24%	17.71%	33.24%	32.18%	15.46%	15.46%
25	β_{weigh}	0	β_{drug}	β_{bon}	0	0	—	—	0.00%	—	—	—	—	—	
26	0	β_{ane}	β_{drug}	β_{bon}	0	0	—	—	0.00%	—	—	—	—	—	
27	β_{weigh}	β_{ane}	0	0	β_{work}	0	—	—	5.07%	0.00%	—	—	—	—	
28	β_{weigh}	0	β_{drug}	0	β_{work}	0	—	—	0.00%	—	—	—	—	—	
29	0	β_{ane}	β_{drug}	0	β_{work}	0	—	—	0.00%	—	—	—	—	—	
30	β_{weigh}	0	0	β_{bon}	β_{work}	0	—	—	8.62%	0.00%	—	—	—	—	
31	0	β_{ane}	0	β_{bon}	β_{work}	0	—	—	0.00%	—	—	—	—	—	
32	0	0	β_{drug}	β_{bon}	β_{work}	0	—	—	8.28%	4.58%	6.22%	4.85%	4.95%	5.03%	5.03%
33	β_{weigh}	β_{ane}	0	0	0	β_{treat}	—	—	—	22.48%	8.39%	0.00%	—	—	
34	β_{weigh}	0	β_{drug}	0	0	β_{treat}	—	—	—	0.00%	—	—	—	—	
35	0	β_{ane}	β_{drug}	0	0	β_{treat}	—	—	—	0.00%	—	—	—	—	
36	β_{weigh}	0	0	β_{bon}	0	β_{treat}	—	—	—	7.96%	3.75%	3.40%	3.59%	3.85%	3.85%
37	0	β_{ane}	0	β_{bon}	0	β_{treat}	—	—	—	0.00%	—	—	—	—	
38	0	0	β_{drug}	β_{bon}	0	β_{treat}	—	—	—	0.00%	—	—	—	—	
39	β_{weigh}	0	0	0	β_{work}	β_{treat}	—	—	—	1.75%	0.00%	—	—	—	
40	0	β_{ane}	0	0	β_{work}	β_{treat}	—	—	—	0.00%	—	—	—	—	

(*Continues*)

Table III. (Continued)

Class no.	Coefficients estimated in the class						Model ANA-1	Model ANA-2	Model ANA-3	Model ANA-4	Model ANA-5	Model ANA-6	Model ANA-7	Model ANA-8	Final ANA Model
41	0	0	β_{drug}	0	β_{work}	β_{treat}	—	—	—	0.00%	—	—	—	—	
42	0	0	0	β_{bon}	β_{work}	β_{treat}	—	—	—	8.27%	3.28%	0.00%	—	—	
	% who ignored three attributes						—	—	***51.35%***	***68.28%***	***39.35%***	***41.49%***	***40.72%***	***24.34%***	***24.34%***
43	β_{weigh}	β_{ane}	0	0	0	0	—	—	—	—	18.54%	11.51%	18.41%	36.47%	36.47%
44	β_{weigh}	0	β_{drug}	0	0	0	—	—	—	—	0.00%	—	—	—	
45	0	β_{ane}	β_{drug}	0	0	0	—	—	—	—	0.00%	—	—	—	
46	β_{weigh}	0	0	β_{bon}	0	0	—	—	—	—	3.72%	3.93%	0.00%	—	
47	0	β_{ane}	0	β_{bon}	0	0	—	—	—	—	0.00%	—	—	—	
48	0	0	β_{drug}	β_{bon}	0	0	—	—	—	—	0.00%	—	—	—	
49	β_{weigh}	0	0	0	β_{work}	0	—	—	—	—	5.30%	2.76%	2.98%	2.82%	2.82%
50	0	β_{ane}	0	0	β_{work}	0	—	—	—	—	—	0.00%	—	—	
51	0	0	β_{drug}	0	β_{work}	0	—	—	—	—	—	0.00%	—	—	
52	0	0	0	β_{bon}	β_{work}	0	—	—	—	—	—	6.97%	0.00%	—	
53	β_{weigh}	0	0	0	0	β_{treat}	—	—	—	—	—	0.00%	—	—	
54	0	β_{ane}	0	0	0	β_{treat}	—	—	—	—	—	2.66%	1.75%	2.34%	2.34%
55	0	0	β_{drug}	0	0	β_{treat}	—	—	—	—	—	0.00%	—	—	—
56	0	0	0	β_{bon}	0	β_{treat}	—	—	—	—	—	—	0.00%	—	—
57	0	0	0	0	β_{work}	β_{treat}	—	—	—	—	—	—	0.00%	—	—
	% who ignored four attributes						—	—	—	—	***27.56%***	***27.83%***	***23.14%***	***41.63%***	***41.63%***
58	β_{weigh}	0	0	0	0	0	—	—	—	—	—	—	0.00%	—	—
59	0	β_{ane}	0	0	0	0	—	—	—	—	—	—	0.00%	—	—
60	0	0	β_{drug}	0	0	0	—	—	—	—	—	—	0.00%	—	—
61	0	0	0	β_{bon}	0	0	—	—	—	—	—	—	11.48%	7.18%	7.18%
62	0	0	0	0	β_{work}	0	—	—	—	—	—	—	—	0.00%	—
63	0	0	0	0	0	β_{treat}	—	—	—	—	—	—	—	0.00%	—
	% who ignored five attributes						—	—	—	—	—	—	***11.48%***	***7.18%***	***7.18%***
64	0	0	0	0	0	0	—	—	—	—	—	—	—	4.68%	4.68%

Table IV. Estimates and model fit of the two approaches

	Standard model		ANA Model final	
	β	SE	β	SE
Constant	0.059	0.054	0.083	0.060
Curative treatment approach	−0.096	0.077	−1.840***	0.540
Drug used: AS–AQ	−0.340***	0.072	−1.572***	0.284
Under-staffing	0.271***	0.082	0.880***	0.244
Low birth weight risk (per % point)	−0.195***	0.016	−0.314***	0.031
Anaemia risk (per % point)	−0.127***	0.006	−0.214***	0.016
Bonus (in GHC)	0.039***	0.008	0.064***	0.022
Log-likelihood	−1076		−1025	
χ^2	794.7 (p < 0.000)		898.1 (p < 0.000)	
Pseudo R^2	0.277		0.304	
AIC	1.02		0.98	
Correctly predicted	67.0%		75.2%	

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

low birth weight, were the most attended (only ignored by 23.5% and 19.2%, respectively), with the financial attribute in between (46.3%). Interestingly, these results are more pessimistic in terms of attribute attendance than the ones obtained with the simple descriptive analysis shown in Table II. However, the hierarchy of importance across all attributes, as measured by the proportion of respondents who attended an attribute, is the same in the two approaches.

4.3. Impact of attribute non-attendance on model estimates, policy and welfare outputs

Table IV reports the model fit statistics and coefficients estimated in the standard logit model and in the final ANA model, whose ten classes encompass all ANA strategies used by the respondents in the DCE. The ANA model shows a significant improvement in model fit compared with the standard model, with a lower log-likelihood and information criteria, higher Mc Fadden's pseudo-R^2 and much better predictions of respondents' choices (75.2% of correct predictions vs. 67.0%).

In terms of model estimates, the models give similar results in terms of the sign and significance of the coefficients, with one exception. The coefficient associated with the treatment approach is significant in the final ANA model, although it is not in the standard model. This result underlines the capacity of LCMs to elicit more heterogeneity in responses than the standard model. Indeed, although most respondents ignored the treatment approach attribute, it had a significant impact on the choices of those respondents who considered it.

To understand the effects of accounting for axiom violations or not, two outcomes typically used by policymakers were produced that are more directly comparable across models than coefficient estimates: WTP estimates and predicted probabilities.

Table V. Willingness-to-pay estimates

	Standard model WTP (95% CI)[a]	Final ANA model WTP (95% CI)[a]	Ratio of WTP estimates[b]
The treatment approach is preventive	2.47 (−1.44 to 6.37)	28.78 (12.20–45.37)	11.65
The drug used is SP	8.75 (5.11–12.39)	24.59 (15.83–33.34)	2.81
Risk of low birth weight in newborns avoided (per % point)	5.03 (4.20–5.85)	4.91 (3.93–5.90)	0.98
Risk of anaemia in pregnant women avoided (per % point)	3.28 (2.95–3.60)	3.35 (2.83–3.88)	1.02

[a]The WTP confidence interval was calculated using the delta method.
[b]Calculated as follows: $WTP_{ANA} / WTP_{standard}$.

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Table VI. Comparison of model predictions under the different specifications (predicted proportion of respondents who would prefer new treatment guidelines to current guidelines)

Scenario	Description of new guidelines	Standard model prediction	Final ANA Model prediction	Ratio of model predictions[a]
1[b]	Current guidelines but new drug (AS–AQ)	40.2	38.5	0.96
2[b]	Current guidelines but curative approach	46.1	44.1	0.96
3[b]	Current guidelines but new drug (AS–AQ) and curative approach	37.9	35.6	0.94
4[b]	Current guidelines but new drug (AS–AQ) and curative approach with higher workload and small bonus (GHC10)	54.1	48.3	0.89
5[c]	Current guidelines but new drug (AS–AQ)	66.7	66.8	1.00
6[c]	Current guidelines but new drug (AS–AQ) and curative approach	64.6	62.4	0.97

[a]Calculated as follows: $P_{ANA} / P_{standard.}$

[b]Under scenarios 1–4, in the current situation, the guidelines for treatment are as follows: preventive approach, use of SP, normal workload and no bonus. This has been shown to lead to the following health outcomes: 10% incidence of low birth weight and 1% incidence of severe anaemia.

[c]Under scenarios 5 and 6, the clinical guidelines for treatment remain the same as defined in scenarios 1 to 4, but resistance to the drug used (SP) would lead to worse health outcomes: 13% incidence of low birth weight and 5% incidence of severe anaemia. In contrast, the new guidelines with a different drug would be associated with better health outcomes: 10% incidence of low birth weight and 1% incidence of severe anaemia.

The WTP estimates obtained for four policy attributes by dividing their parameters by the bonus parameter are reported in Table V, both for the standard model and the final ANA model. In examining Table V, visible differences appear in the WTP estimates derived from the two models, as assessed by the WTP ratios presented in the last column. Three of four ratios are greater than 1, meaning that WTP estimates for the ANA model are higher, sometimes quite dramatically so (for the treatment approach the WTP is almost 12 times higher in the ANA model). However, as shown by the overlapping confidence intervals and the ratios close to one, the WTP estimates are quite similar for the two health outcomes.

Turning to a different output that can be relevant for policymakers, one predicted the proportion of respondents who would prefer to adopt a new set of clinical guidelines that would modify their job (compared with the current ones) but would yield similar health outcomes (scenarios 1—4). Furthermore, in scenarios 5 and 6, similar policy changes were simulated but in the context of drug resistance, which would compromise the efficacy of the current guidelines (Lagarde *et al*., 2011). The predictions obtained for these six simulations under the two models are reported in Table VI.

Unlike some of the results obtained for the WTP estimates, the two models yield very similar predictions. All ratios of predicted probabilities (last column of Table VI) are very close to 1, between 0.89 and 1.00. All ratios (except one) are slightly lower than 1, meaning that the standard model concluded that a somewhat higher proportion of respondents would prefer the new guidelines.

5. DISCUSSION

Overall, the results of this analysis of ANA patterns in a DCE administered to healthcare providers in Ghana concur with findings from the nascent literature on heuristics in DCEs, in which evidence is mounting to show that respondents do not comply with the axiom of continuous preferences.

Findings show that only 2.6% of the respondents made trade-offs between all attributes when choosing between the two hypothetical scenarios proposed. This result is similar, and even slightly more optimistic, than the one obtained by the only other comparable study[1] (Campbell *et al*., 2010) where only 0.6% of the respondents had considered all attributes. The aggregate membership probability for considering only one and two

[1]The study by Campbell *et al*. is the only one that depicts the frequency of all possible ANA rules employed by respondents. However, there were only five attributes in that study, against six in the DCE analysed here.

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attributes was 48.8 % (7.2% and 41.6%, respectively) in this study, against 47.8% (22.4% and 25.4%) in Campbell *et al*. (2010). These strikingly similar findings confirm that respondents in DCEs make their decisions based on little information.

Also in line with previous studies (Hess and Rose, 2007; Scarpa *et al*., 2009; Campbell *et al*., 2010; Hensher and Greene, 2010; Hole, 2011b), this study finds that accounting for ANA strategies improved the goodness-of-fit of the model and affected the significance and strengths of some preferences as measured by the estimated coefficients. As a result, WTP estimates sometimes differed when accounting for ANA, compared with the standard analysis. These results question the use of WTP estimates, particularly in the context of economic analyses. This study and others suggest not only that the assumption that respondents trade off all the attributes is incorrect but also that often only a fraction of the respondents take the cost attribute into account in their decision-making process (here, 46.3%). Therefore, inferring anything about the willingness to pay of *all* respondents is misleading, and researchers should try to reflect better the heterogeneity of valuations.

In contrast to WTP estimates, the behavioural predictions of the different models, simulating the proportion of respondents who would prefer a new set of guidelines to the current policy, showed that ignoring ANA had little impact. Indeed, the discrepancies between the predictions of the two models differed by only a few percentage points at most. If this result is confirmed by other studies, it is reassuring for the reliability of the health policy recommendations based on DCE predictions in studies that have not accounted for ANA rules (see, e.g. Goto *et al*., 2007; Gerard *et al*., 2008; Blaauw *et al*., 2010).

The quantitative analysis of attribute processing strategies is a growing field of research in transport and environment economics, but it remains to be more widely studied in health economics. This paper suggests at least two avenues of research for health economists involved in DCEs.

First, it would be interesting to perform similar analyses in different contexts, in particular with different respondents. Here, the analysis drew on the responses given by a small sample of low-level and mid-level cadres in antenatal care wards in Ghana. The characteristics associated with such a specific sample (lower level of responsibilities and education, little familiarity with DCE surveys) may have increased the presence of ANA.

Second, it would be valuable to understand better the motives for ignoring attributes. In some studies, authors have hypothesised that individuals ignored attributes that were irrelevant or less meaningful than others. It was maybe the case here where respondents less frequently ignored health outcomes and financial incentives. In other studies, respondents ignored one attribute (cost) to signify their refusal to trade between money and other valued goods, such as the environment (Carlsson *et al*., 2010). Research on decision-making processes (Payne *et al*., 1993) has underlined that heuristics are likely to be influenced by the decision problem itself (e.g. its complexity), respondent-specific characteristics (e.g. familiarity to the choice task, cognitive skills) and the broader context in which the choice task is taken (e.g. time pressure). It would be important to tease out the relative role of these factors and, particularly, to learn whether ANA in DCEs is the result of actual preferences or whether it is a coping mechanism used by respondents to tackle a complex task, performed under time constraints. If the latter explanation prevails, this could bring doubts about the external reliability of DCEs. Further in-depth qualitative work, akin to the approach taken by Ryan *et al*. (2009) is likely to provide interesting responses to these questions.

In a rapidly evolving field, a lot of the methodological debate in DCEs has focused on advances in the generation of experimental design (Street and Burgess, 2007). The increasing sophistication of econometric tools available to the analyst to estimate choice models has recently started to shift the focus back to the respondents and the choice processes they employ to make their choices. Health economists have often debated whether respondents displaying discontinuous preferences should be incorporated in the analysis because they violate utility axioms (McIntosh and Ryan, 2002; Scott, 2002) or whether these dominant preferences might be actual preferences (Lancsar and Louviere, 2006) and, therefore, kept in the analysis. The analysis of discrete choice experiments with latent class models accounting for attribute non-attendance provides an appealing analytical response to this debate.

CONFLICT OF INTEREST

The author declares no conflicts of interest.

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