Attribute Non-Attendance in Discrete Choice Experiments: Evidence from Farmers' Choice Decisions for Sweet Potato Varietal Traits in Kenya

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Abstract
The objective of this study was to contribute to our better understanding of farmers' attribute non-attendance in their choice decisions for sweet potato varietal traits in Kenya. This was achieved by evaluating both stated and inferred attribute non-attendance in a discrete choice experiment of farmers' in Western Kenya that involved six sweet potato varietal traits, namely: yield level, tolerance to pests and diseases, sweetness of the flesh, color of the flesh, maturity period and price. Empirical results from 400 randomly selected farmers indicate that flesh color was the most ignored attribute from both self-reported (61.8%) and inferred (59.2%) attribute non-attendance. There was also a considerable mismatch between self-reported and inferred attribute non-attendance values. The study found improvement in model fit when attribute non-attendance was taken into account, therefore implying that it is critical to account for attribute non-attendance in policy studies involving discrete choice experiments.

Keywords: Attribute non-attendance, discrete choice experiment, sweet potato variety
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1. Introduction

Conventionally, discrete choice experiments (DCEs) usually present respondents with a series of choice questions where each present a number of alternatives. Each of the alternatives is described in terms of multiple attributes of varying levels. Respondents are then asked to choose their preferred alternative in each set. A key assumption in the analysis of choice data has been that of infinite substitutability between the attributes. This is known as the continuity axiom, which implies that respondents base their choice on all the attributes presented in a choice set, trading off gains in one attribute to losses in another. In the recent past, empirical evidence shows that respondents may not necessarily weight up all the attributes and their levels, but base their choice on a selection of attributes (Hensher 2006a). This behavior is referred to as attribute non-attendance (ANA), which is perceived in DCEs as discontinuous preference ordering (e.g. McIntosh and Ryan 2002) or lexicographic choices (e.g. Salensminde 2002).

The idea of ANA means that respondents do not make complete trade-offs between all the attributes presented thereby violating the axiom of continuity. Failure to recognize ANA can lead to erroneous and biased welfare estimates, because for those individual respondents who ignore certain attributes, marginal rates of substitution between attributes cannot be calculated (e.g. Scarpa et al. 2009; Hensher et al. 2011). Some underlying reasons for ANA include: a genuine disinterest in the attribute; 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; respondents' different capabilities and motivations and strategic behavior respondents may exhibit, especially in public policy choices, such as innovation prioritization in a publicly-funded healthcare system, among others (Alemu et al., 2013; Hensher et al., 2005, 2012; Hole, 2011; Scarpa et al. 2009).

Notably, ANA may be detected through inspection of individual answers to check whether respondents consistently chose alternatives that were best with respect to one or more attributes. Therefore, the researcher needs to specify decision rules that define what constitutes an inconsistent choice (e.g., McIntosh and Ryan 2002; Sælensminde 2002; Lancsar and Louviere 2006; Hensher and Collins 2011). The other approach that may be used to identify ANA is through supplementary questions, which ask respondents to state which attributes they attended to or ignored when deciding on their preferred option (e.g. Campbell et al., 2008, Hensher et al., 2005, Rose et al., 2005). This is what is called stated non-attendance. A third approach, which has been more explored in the recent past involves the use of modelling procedures that enable a researcher to infer ANA by implicitly estimating the probability that a respondent ignores one or more attributes when making their choice (Hole, 2011). There is evidence that this inferred non-attendance is not necessarily consistent with the responses given to supplementary questions about attribute attendance (Hensher et al., 2011; Lancsar and Louviere, 2006).

In the empirical literature on ANA, there are different modeling procedures that researchers have used to account for ANA in data analysis. The first method simply involves deleting respondents that did not attend to all attributes. This method is not recommended in practice as it may lead to biases and most potentially reduce the representativeness of the study sample. The second method involves the use of the stated non-attendance. Given that ANA may affect the estimated taste parameters, the researcher has to weigh the attribute parameters, based on whether or not the attribute was considered by the respondent (Hensher et al. 2005a). The third method entails the specification of models that infer non-attendance. In this case, the attribute coefficients are constrained to zero, but class probabilities are estimated in the model. Nonetheless, and as earlier stated, inferred non-attendance may not necessarily be consistent with responses given to supplementary questions asked about attribute attendance (e.g. Hensher et al., 2011). While some researchers have tended to use the equality constrained latent class models (ECLC) to account for ANA (e.g. Scarpa et al., 2009, 2011; Hensher et al., 2011), others have used the endogenous attribute attendance (EAA) model to account for non attendance (e.g. Hole, 2011). What is not well known, however, is how these different model specifications that address ANA would perform using data contextualized in a developing country. With most of the available studies on ANA having been conducted in the developed countries (e.g. Kragt, 2013), we are not aware of any study that has modeled ANA with discrete choice data from a developing country and in particular Kenya.

Therefore, this paper used discrete choice data to investigate farmers' preferences for sweet potato varietal traits in Kenya to infer ANA based on the ECLC model. The paper focused on the ECLC model specification for ANA by defining all possible utility functions that could be followed by respondents, given the product attributes provided in the DCE. The paper thus contributes to the stated preference literature by highlighting how best ECLC model specification for ANA best fits data from a developing country and thereby help DCE practitioners to address ANA in their applications.

The rest of the paper is organized as follows. Section 2 provides past literature on ANA. Section 3 describes the econometric modelling techniques used in the analysis of ANA. Section 4 gives a brief description of the experimental design. Section 5 presents the results and discussions and section 6 concludes.

2. Past empirical studies on attribute non attendance

Past empirical studies on attribute non-attendance in stated preference studies can broadly be divided into two main approaches, namely: the stated non-attendance approach and the inferred non-attendance approach. The former involves asking respondents directly whether they have considered all attributes describing the alternatives of the choice tasks or whether they have ignored one or more attributes while choosing among them. It is usually investigated using a binary response variable with the information on ANA commonly being collected after answering all choice sets. Alternatively, non-attendance questions may be asked after each choice set (e.g. Scarpa et al., 2009). The answers to these questions are then used to put certain restrictions on Random Utility models (RUMs).

The first studies to investigate ANA (e.g. Hensher et al., 2005) used the answers to a binary non-attendance question to specify a mixed logit model in which respondents who stated that they ignored a certain attribute were expected to have zero utility. This approach of individual-level zero marginal utility weights has subsequently been applied in several other studies including Hensher (2006), Hensher et al. (2007) and Kragt (2013). The other way used to incorporate information gained from a stated non-attendance question into RUMs has been to estimate different coefficients for each attribute; one for the group of respondents who state that they did not ignore the attributes and one for those who state that they ignored (Hess and Hensher, 2010; Scarpa et al., 2013; Colombo et al., 2013).

Nonetheless, the dependability of the stated ANA approach has been put into question for a number of reasons. First, it has been argued that respondents may assign low importance to an attribute yet, state that they ignored it completely (e.g. Hess and Hensher, 2010) leading to an overestimation of ANA (Carlsson et al., 2010). However, there are some instances in the empirical literature where respondents who report having ignored an attribute were found indeed to have zero marginal utility for the attribute in question (e.g. Balcombe et al., 2011). Second, directly incorporating responses about non-attendance questions into the RUM may cause potential problems of endogeneity bias (e.g. Hess and Hensher, 2010). Third, there is more literature raising the 'still unanswered' question about the liability of complementary questions regarding non-attendance (e.g. Hensher and Rose, 2009; Hensher and Greene, 2010). With the limitations of the stated non-attendance approach, there has been increasing interest in the literature that analyzes different methods of inferring ANA. These studies infer ANA from data using diverse econometric procedures.

The most popular modelling approach that has been implemented consists of latent class models where a probabilistic decision process is used to capture the attendance to attributes and thereby impose specific restrictions on the utility expressions for each class. The majority of studies using discrete probability distributions have used the ECLC models where ANA is operationalized by allowing some respondents to belong to latent classes with zero utility weights for selected attributes, while non-zero parameters are assumed to take the same values across classes (e.g. Scarpa et al., 2009, 2013; Hensher and Greene, 2010; Campbell et al., 2011; Hess et al., 2013). Nonetheless, Hess et al. (2013) argue that the latent class method so far applied in

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DCEs might be misguided as the results might be confounded with regular taste heterogeneity. They suggest instead a combined LC mixed logit model that allows jointly for ANA and continuous taste heterogeneity. One of their findings is that non-attendance is substantially reduced in these models. Similarly, Hensher et al. (2013) presented different latent class models accounting not only for ANA, but also for aggregation of common-metric attributes. One of their models involves several full attendance classes while other classes account for ANA regarding certain attributes. The model does not constrain the parameters to be equal across classes. In the next step they add to this model an additional layer of heterogeneity by specifying some parameters to follow a random distribution. For their data, they found that accounting additionally for taste heterogeneity through random parameters within a latent class only marginally improves the model, but increases the probability of membership to full attribute attendance classes. Collins et al. (2013) also presented a generalized random parameters ANA model (RPANA) as an alternative approach. They found that with stated ANA as covariates, the model performance was improved.

Studies that employ both the stated non-attendance and the inferred non-attendance approach are Hensher et al. (2007), Hensher and Rose (2009), Campbell et al. (2011), Kragt (2013) and Scarpa et al. (2013). The overall finding is that results from inferred and stated ANA are not consistent, and that the inferred approach provides a better model fit. However, regardless of the modelling approach, almost all studies find that accounting for ANA improves model and that respondents indeed apply different information processing strategies (e.g. Hensher et al., 2005; Hess and Hensher, 2010; Scarpa et al., 2013). Moreover, accounting for ANA leads to significantly different willingness to pay estimates which may be lower (e.g. Hensher, 2006; Campbell et al., 2008; Scarpa et al., 2009) or higher (e.g. Hensher et al., 2005; Hensher and Rose, 2009; Hensher and Greene, 2010; Lagarde, 2013).

While majority of studies dealing with ANA suggest that taking non attendance into account is likely to improve model performance and potentially impact on the WTP estimates, the results in the literature are equivocal. There is no general consensus on exactly how ANA should be dealt with. However, a general agreement exists that ignoring ANA may considerably lead to biased and inaccurate welfare estimates and poor model performance. With all studies investigating ANA agreeing that respondents do ignore attributes to some extent, the most important research question therefore is not whether or not respondents ignore attributes but rather how different models dealing with ANA compare. In the context of inferred ANA, this paper attempted to understand how ECLC (Scarpa et al., 2009; Hensher et al, 2011) and EAA (Hole, 2011) models compare. This would help in the search for an appropriate model specification that best fits the data and therefore contribute to enrichment of empirical literature on DCEs.

3. Econometric models

3.1. Accounting for stated ANA

Following Kragt (2013), different kinds of models were estimated in this study so as to account for both stated and inferred attribute non attendance. To begin with, a set of mixed logit (MXL) models were first estimated to account for unobserved individual preference heterogeneity in the sampled population (e.g. Hensher et al., 2005). Heterogeneity is, in this case, accounted for by specifying random parameters β_{ik} for the k^{th} attribute faced by the i^{th} individual as:

$$\beta_{ik} = \beta_k + \sigma_k v_{ik} \quad (1)$$

where β_k is the unconditional population parameter of the preference distribution; and v_{ik} are random, unobserved variations in individual preferences that are distributed around the population mean with standard deviation σ_k. Individual taste differences in the population are represented by density function $f(\beta_i|\theta)$ (e.g. Hensher et al., 2005), where θ is a vector of parameters characterising the density function that captures individual deviations from the mean. The researcher specifies a distributional form for θ (e.g. Hensher et al., 2005; Hensher and Greene, 2003). In the present study, the sweet potato varietal attributes were defined as random, normally distributed parameters while the cost attribute as a random parameter with a constrained triangular distribution. In the MXL model, the unconditional probability of observing choice j by the i^{th} individual in choice situation t is equal to the expected value of the logit probability over the parameter values. This is the integral over all possible values of β_i, weighed by the density of β_i (e.g. Hensher et al., 2005), that is:

$$E(Prob_{ijt}) = \int Prob_{ijt}(\beta_i).f(\beta_i|\theta)d\beta_i \quad (2)$$

Since equation (2) lacks a closed form solution, the model is best estimated using the simulated maximum likelihood approaches (e.g. McFadden and Train, 2000). The MXL models in this study were estimated in a panel format, and included an additional latent error component that was common between the two change alternatives. This error component allows for cross-correlation between the stochastic components of the utilities derived from those alternatives. It can capture unobserved heterogeneity that is alternative- rather than individual-specific (e.g. Greene and Hensher, 2007). The error component appears as $M \leq J$ additional random effects:

$U_{ijt} = \beta^{'}_{i}X_{ijt} + \varepsilon_{ijt} + d_{jm}w_{im}$; $m = 1, \ldots, M \leq$ (3)

where w_{im} are normally distributed latent effects with zero mean; and d_{jm} = 1 if the random error component appears in the utility function for j. As for ANA, it is accounted for by restricting the attribute coefficients to zero if an attribute was ignored by the respondent as captured through the supplementary questions. This is readily implemented in the NLOGIT software coding the attributes as "-888" if respondent did not attend to the attribute. It is an important part of the underlying theory that the attribute coefficients, rather than the attribute levels, are constrained to zero (e.g. Hensher et al., 2012). Although some authors have claimed that the two approaches are essentially the same, setting attribute levels to zero if ignored will still result in estimated taste parameters, whereas setting coefficients to zero means that the respondent did not attach any weight to that attribute in evaluating the utility derived from an alternative (see Hensher et al., 2005) for a more detailed description of the MXL model that incorporates ANA.

3.2. Accounting for inferred ANA

Notably, it is very likely that there may be a correlation between respondents' self-reported serial non-attendance and other unobserved components meaning that using respondents' ANA statements could lead to endogeneity issues which could in turn lead to biased parameter estimates (e.g. Hess and Hensher, 2012b). Moreover, behavioral economists posits that verbal responses to survey questions may not always be a good indicator of the actual behavior (e.g. Armitage and Conner, 2001; Ajzen et al., 2004) and as such, it has been acclaimed that stated ANA may not be a reliable measure of attendance (e.g. Hensher et al., 2012; Scarpa et al., 2011). To explore this suggestion in the present study, the equality constrained latent class model (ECLC) was estimated where ANA was inferred from respondents' observed choices. In the ECLC model, the population of interest is divided into a discrete number of classes, with number of classes being determined endogenously from the data. Preferences of individuals are assumed to be homogeneous within a class but can vary between classes. As in Kragt (2013), the utility that the i^{th} individual derives from choice alternative j in choice situation t may be defined as:

$U_{ijt} = \beta^{'}_{c}X_{ijt} + \varepsilon_{ijt}$ (3)

where a class specific parameter vector β_c is estimated in the model. The probability of choosing alternative j is now conditional on belonging to a certain class c algebraically given as:

$Prob(j_{it}|c) = \frac{\exp(\mu_c \beta^{'}_{c} X_{ijt})}{\sum_{q=1}^{j} \exp(\mu_c \beta^{'}_{c} X_{iqt})}$ (4)

where μ_c is a class specific scale parameter. The error terms are assumed to be iid across individuals and classes with a type *1* extreme value distribution and scale factor ϕ. Class probabilities can be specified by the logit formula:

$Prob(j_{it}|c) = \frac{\exp(\phi \gamma^{'}_{c} Z_i)}{\sum_{s=1}^{c} \exp(\phi \gamma^{'}_{s} Z_i)}$ (5)

where Z_i is a vector of choice invariant individual-specific characteristics; γ_c is a vector of parameters to be estimated in the model; and c is the total number of classes specified by the researcher. As such, accounting for ANA requires the researcher to specify a number of classes in which some attribute coefficients are restricted to zero. Respondents whose choice strategies match that of the specified pattern of non-attendance are said to have a higher predicted probability of belonging to that class. The model infers class probability, and thus probability of non-attendance, from respondents' observed choices (e.g. Scarpa et al., 2009; Campbell et al., 2010; Hensher et al., 2012). In this study, ANA was inferred by identifying $2^k = 2^6 = 64$ latent classes in the ECLC models. These were associated with all the possible different combinations of ANA to the six choice attributes used in the study.

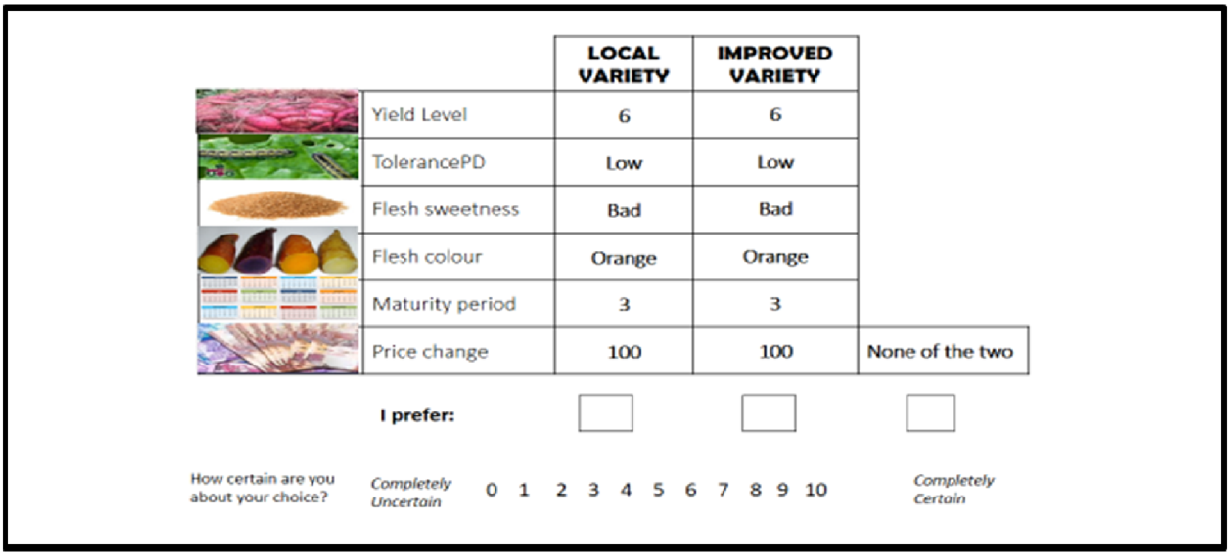
4. Experimental design

In DCEs, respondents are presented with alternative descriptions of policy interventions, differentiated by different combinations of attribute levels. Respondents are then asked to choose their preferred alternative. For each choice made, the alternative selected is assumed to yield a higher level of satisfaction than that rejected. This enables the probability of an alternative being chosen to be modelled in terms of the attribute levels used to describe the policy intervention. In this paper, respondents were presented a series of variety traits that include: yield level, tolerance to pests and diseases, sweetness of the flesh, color of the flesh, maturity period and price. Respondents were asked to choose their most preferred varietal alternative. Based on expert interviews in an open-ended pretest ($N = 50$), different levels for the selected varietal traits were selected as shown in Table 1. below.

Table 1: Descriptions and levels of the chosen attributes

Attribute	**Description**	**Levels**
Yield	The amount of sweet potato out per hectare	Level 1: 6 tons/hactre Level 2: 10 tons/hactre Level 3: 14 tons/hactre
Tolerance	Forbearance to common crop pests and diseases	Level 1: High Level 2: Medium Level 3: Low
Sweetness	Taste of the sweet potato flesh.	Level 1: Good Level 2: Average Level 3: Bad
Colour	Colour appearance of the sweet potato flesh.	Level 1: Orange Level 2: Yellow Level 3: White
Maturity	Period sweet potato takes to mature.	Level 1: Upto 3 months Level 2: Upto 5 months Level 3: Upto 7 months
Price	Change in price per unit of output.	Level 1: 100 Level 2: 200 Level 3: 300

There were also different alternative varietal scenarios created by combining these six variables based on their different attribute levels. Because respondents cannot be shown all different choice options, the number of possible combinations was reduced to 10 choice sets of 10 choice tasks each based on an orthogonal fractional factorial design generated in the statistical software *Ngene*, enabling the estimation of main effects and two-way interactions. Each respondent was randomly shown one of these 10 choice sets of 10 choice cards. Each choice card shows two hypothetical choice alternatives describing a future policy scenario along with the option to choose none of the two.



Inclusion of this latter 'status quo' alternative is instrumental to be able to estimate welfare measures that are consistent with demand theory (Bateman et al., 2003). It was emphasized that respondents would not have to pay anything extra if they choose the opt-out. An example of a choice card is presented in Figure 1.

The design of the choice experiment main comprised three sections. The first section was intended to measure respondents' general knowledge on sweet potato varietal traits so as to familiarize them with the attributes of interest that were being evaluated. The second section contained questions for DCE analysis that were designed to elicit respondents' WTP for sweet potato varietal traits by estimating trade-offs between price and the other attributes. In this case, common photographs of the attributes were also inserted in the DCE cards to enhance respondents' understanding regarding the attributes. The final part elicited socio-demographic information of the respondents such as age, gender, education and income. The choice experiment instrument was first pre-tested and subsequently implemented between October – December 2019 through 400 in-person interviews in Western Kenya. The response rate was 100%, which is not unusual for this kind of stated preference research in a developing country (Whittington, 1998). A predetermined random sampling plan was used to obtain respondents for the survey. Trained local enumerators were also used for the interviews to ensure choice scenarios were presented to respondents in a more informative way. The enumerators had instructions to limit all explanations to facts so as to minimize the introduction of any interviewer bias. Moreover, respondents were given adequate time to understand and answer each question so as to enhance the validity of responses obtained. SurveyCTO, an online interactive means of capturing data using smartphone was employed. The results are presented in the following section.

5. Results and discussion

5.1 Descriptive results

Descriptive results of the socio-demographic and farm characteristics of the survey sample are presented in Table 2. As shown, the mean age of the respondents was 45 years with men accounting for the largest share (78%) of the respondents. Most respondents (93%) had primary and post-primary level of education with only 11% and 14% of the respondents having had access to farm credit and agricultural extension services, respectively. On average, the distance to a reliable input/output market centre was about 3kms with membership to farm organizations having a share of 16% of the interviewed farmers.

Table 2: Socio-demographic and farm characteristics of the survey sample

Variable	Mean/proportion	Std error	Min	Max
Age (years)	45	13.31	20	85
Gender (1=male)	0.78	0.41	0	1
Education (1=educated)	0.93	0.25	0	1
Access to farm credit (1=access)	0.11	0.31	0	1
Access to agricultural extension (1=access)	0.14	0.35	0	1
Membership to farm organizations (1=member)	0.16	0.37	0	1
Sweet potato variety grown (1=improved)	0.62	0.48	0	1
Frequency of growing sweet potatoes (1=more than once)	0.36	0.48	0	1
Sweet potato use (1=commercial purposes)	0.95	0.22	0	1
Source of sweet potato vines (1=own farm)	0.35	0.77	0	1
Quantity of sweet potato harvest (tonnes)	1.91	15.23	0	300
Sweet potato income (KES)	11,702	2,114	0	180,000
Distance to reliable input/output market (Kms)	3.07	0.71	0.1	7

Land holdings were, on average, 0.37 acres with household heads having a farming experience of about The study also found that 62% of the respondents were growing improved sweet potatoes varieties with 36% of the respondents saying they grew sweet potatoes more than once in a year. Moreover, the study also found that 95% of the interviewed farmers produced sweet potatoes for commercial purposes. As to the source of the sweet potato vines, the study found that 35% of the farmers sourced vines from their own farms. On average, sweet potato production was about 1.91 tonnes that fetched an average income of about KES 11,702.

In addition, the descriptive results with detailed analysis of attribute attendance are presented in Table 2. As shown, about 21% of respondents considered all the attributes in their choice decisions. However, the study found that respondents, as per their self-reported attendance, ignored different sweet potato varietal attributes in their choice decisions while nearly all of them showed lexicographic preferences towards only one attribute. The least attended attribute was 'yield' (ignored by 7% of respondents), followed by 'flesh colour' (ignored by 12.3% of respondents) and then tolerance to pests and diseases (ignored by 17% of the respondents). The most ignored attribute was flesh colour (ignored by 61.8% of the respondents). About 42.3% of the respondents ignored the price change attribute, which means that there was no considerable varietal traits and price trade-offs for these respondents.

Table 3: Stated attribute non attendance of the survey sample

Variable	Number of respondents	% of the total
Attended to all attributes		
Yield, tolerance, flesh taste, flesh colour, maturity period, price change	85	21.3
Ignored one attribute		
Yield level	28	7.0
Tolerance level	68	17.0
Flesh taste	81	20.3
Flesh colour	247	61.8
Maturity period	49	12.3
Price change	169	42.3
Ignored two attributes		
Yield and tolerance level	7	1.8

Yield and flesh taste	9	2.3
Yield and flesh colour	22	5.5
Yield and maturity period	2	0.5
Yield and price chance	14	3.5
Tolerance level and flesh taste	11	2.8
Tolerance level and flesh colour	49	12.3
Tolerance level and maturity period	17	4.3
Tolerance level and price change	34	8.5
Flesh taste and flesh colour	67	16.8
Flesh taste and maturity period	13	3.3
Flesh taste and price change	47	11.8
Flesh colour and maturity period	42	10.5
Flesh colour and price change	123	30.8
Maturity period and price change	30	7.5
Ignored three attributes		
Yield, tolerance, flesh taste	1	0.3
Yield, tolerance, flesh colour	5	1.3
Yield, tolerance, maturity period	1	0.3
Yield, tolerance, price change	4	1.0
Tolerance, flesh taste, flesh colour	9	2.3
Tolerance, flesh taste, maturity period	6	1.5
Tolerance, flesh taste, price change	8	2.0
Flesh taste, flesh colour, maturity period	12	3.0
Flesh taste, flesh colour, price change	39	9.8
Flesh colour, maturity period, price change	26	6.5
Ignored four attributes		
Yield, tolerance, flesh taste, flesh colour	1	0.3
Yield, tolerance, flesh taste, maturity period	1	0.3
Yield, tolerance, flesh taste, price change	1	0.3
Tolerance, flesh taste, flesh colour, maturity period	6	1.5
Tolerance, flesh taste, flesh colour, price change	6	1.5
Flesh taste, flesh colour, maturity period, price change	9	2.3
Ignored five attributes		
Yield, tolerance, flesh taste, flesh colour, maturity period	1	0.3
Yield, tolerance, flesh taste, flesh colour, price change	1	0.3
Tolerance, flesh taste, flesh colour, maturity period, price change	4	1.0
Ignored all attributes		
Yield, tolerance, flesh taste, flesh colour, maturity period, price change	0	0.0

5.2 Econometric results

In this section, results of the stated non-attendance estimated through MNL and MXL models and the inferred non-attendance estimated through ECLC models are shown. The MNL-ANA and MXL-ANA models account for non-attendance by constraining the attribute parameters to zero if the respondent said that they had not considered that attribute. An alternative specific constant (ASC) is included in the utility function for the two 'sweet potato variety' alternatives (local and improved). As the interest of research in this paper lies in evaluating ANA, only results of ANA models that do not include socio-demographics are reported.

As shown in table 4, the results are fundamentally as expected with all coefficients estimates showing the expected signs and acceptable levels of statistical significance. The ASC parameter is positive, which implies that respondents, on average, prefer the cultivation of the two sweet potato varieties as opposed to the status quo option (no cultivation of either of the sweet potato varieties). There is also substantial improvement in model fit (in terms of log-likelihood, McFadden Pseudo R^2 and the Akaike information criteria) when moving from a MNL to a MXL models.

Table 4: Results of MNL and MXL models on respondents' self-reported attribute attendance

Descriptions	Not Accounting for ANA				Accounting for ANA			
	MNL - Standard Model		MXL- Standard Model		MNL – ANA Model		MXL– ANA Model	
	Coef.	Std error	Coef.	Std error	Coef.	Std error	Coef.	Std error
ASC (1 = non-status quo)	2.806***	0.1674	3.2608***	3.2608	2.499**	0.147	3.936***	0.276
Yield level (1 = high)	0.041***	0.0069	0.0394***	0.0394	0.056***	0.007	0.049***	0.007
Tolerance to pests and diseases (1 = high)	0.079***	0.0269	0.0750***	-0.0750	0.038**	0.029	0.052*	0.030
Sweetness of flesh (1 = good)	0.106***	0.0272	0.0985***	-0.0985	0.076***	0.029	0.086***	0.031
Colour of flesh (1 = appealing)	0.038	0.0275	0.0294	0.0294	0.119**	0.041	0.077*	0.044
Maturity period (1 = longer)	-0.052***	0.0136	-0.0522***	-0.0522	-0.060***	0.014	-0.059***	0.015
Price change (1 = high)	-0.0003	0.0003	-0.0002	-0.0002	-0.0003	0.0004	-0.0001	0.0004
Standard deviation of random parameters								
ASC			0.9091**	0.212			2.549***	0.2470
Yield level			0.0575***	0.013			0.026**	0.0122
Tolerance to pests and diseases			0.0530*	0.040			0.066*	0.0385
Sweetness of flesh			0.0786**	0.040			0.024**	0.0483
Colour of flesh			0.0469**	0.039			0.072*	0.0520
Maturity period			0.0089**	0.025			.0310*	0.0179
Price change			0.0032*	0.001			0.000*	0.0009
Model summary statistics								
Log-likelihood	-3246.79		-3208.73		-3235.55		-3170.51	
LR chi-square	101.15		2371.44		63.95		2347.88	
Prob > chi square	0.0000		0.0000		0.0000		0.0000	
McFadden Pseudo R^2	0.0432		0.2698		0.0487		0.2785	
Akaike Information Criterion (AIC)	6507.60		6445.50		6485.10		6369.00	
Number of observations	4000		4000		4000		4000	
Parameters	7		14		7		14	

Explanatory notes: $* p < 0.1$; $** p < 0.05$; $*** p < 0.0$

The standard deviations on the random parameters are significant, implying that there is considerable unobserved heterogeneity in the preferences across respondents. The latent error component in the MXL models is significant, indicating unobserved differences in the error variance associated with the two sweet potato varietal alternatives compared to the base alternative.

Notably, The MNL and MXL models rely on respondents' self-reported attribute attendance. Recent literature (e.g. Hensher et al., 2012; Scarpa et al., 2011) has suggested that the responses given to supplementary questions may not be consistent with ANA inferred from statistical models. This inconsistency is explored in the present study by specifying ECLC model, where class membership is estimated endogenously. The specification search started with a full 64-class ECLC model, gradually eliminating classes with very low predicted class probabilities and accounting for changes in the Akaike information criteria (AIC). With evidence of unobserved preference heterogeneity in the estimated MXL model, an ECLC model that incorporates preference heterogeneity between classes was explored by estimating class-specific taste parameters. Based on balancing improvements in model fit, while limiting classes with very small probabilities, a seven-class ECLC model was found to fit the dataset best. The seven classes of ANA were: (i) full attendance (ii) ignored yield (iii) ignored tolerance (iv) ignored flesh taste (v) ignored flesh colour (vi) ignored maturity period (vii) ignored price change. The ECLC class probabilities provide an indication of the proportion of respondents that are likely to fall in each class. By comparing the predicted probabilities of the seven-class ECLC model in Table 5 to respondents' stated ANA in Table 3, the study found considerably large variations between the predicted class probabilities and self-reported ANA. For instance, 2.1% of respondents is predicted to have attend to all attributes compared to 21.3% in the self-reported attendance. The model also predicts that about 20% of respondents based their choice decisions solely on yield level as opposed to 7% in the self- reported attendance. Considerable discrepancies between predicted and self-reported values are also seen among respondents in their choice decisions for the other varietal attributes. Of interest, however, is that about 59.2% of respondents is predicted to have ignored the flesh color attribute, which compares well with 61.8% in the self-reported attendance.

Table 5: ECLC model results on ANA for sweet potato varietal traits in Western Kenya

Choice	Parameter	Std error
	Latent class 1	
ASC	2.985***	0.222
Yield level	0.095***	0.011
Tolerance	-0.099	0.070
Sweetness of flesh	-0.118	0.076
Colour of flesh	0.034	0.081
Maturity period	-0.122***	0.035
Price change	-0.0005	0.001
	Latent Class 2	
ASC	2.985***	0.222
Yield level	0.0	Fixed
Tolerance	-0.099	0.070
Sweetness of flesh	-0.118	0.076
Colour of flesh	0.034	0.081
Maturity period	-0.122***	0.035
Price change	-0.0005	0.001
	Latent class 3	
ASC	2.985***	0.222
Yield level	0.095***	0.011
Tolerance	0.0	Fixed
Sweetness of flesh	-0.118	0.076
Colour of flesh	0.034	0.081
Maturity period	-0.122***	0.035
Price change	-0.0005	0.001
	Latent class 4	
ASC	2.985***	0.222
Yield level	0.095***	0.011
Tolerance	-0.099	0.070
Sweetness of flesh	0.0	Fixed
Colour of flesh	0.034	0.081
Maturity period	-0.122***	0.035
Price change	-0.0005	0.001
	Latent class 5	
ASC	2.985***	0.222
Yield level	0.095***	0.011
Tolerance	-0.099	0.070
Sweetness of flesh	-0.118	0.076
Colour of flesh	0.0	Fixed
Maturity period	-0.122***	0.035
Price change	-0.0005	0.001
	Latent class 6	
ASC	2.985***	0.222
Yield level	0.095***	0.011
Tolerance	-0.099	0.070
Sweetness of flesh	-0.118	0.076
Colour of flesh	0.034	0.081
Maturity period	0.0	Fixed
Price change	-0.0005	0.001
	Latent class 7	
ASC	2.985***	0.222
Yield level	0.095***	0.011
Tolerance	-0.099	0.070
Sweetness of flesh	-0.118	0.076
Colour of flesh	0.034	0.081

Choice	Parameter	Std error
Maturity period	-0.122***	0.035
Price change	0.0	Fixed
Estimated class probabilities		
Probability - class 1	0.021	3.564
Probability - class 2	0.200**	0.091
Probability - class 3	0.062	0.690
Probability - class 4	0.050	0.635
Probability - class 5	0.592	2.358
Probability - class 6	0.015***	0.157
Probability - class 7	0.061	1.447
Model summary statistics		
Log-likelihood	-3212.67	
LR chi-square (12 d.o.f.)	2363.56	
Prob > chi square	0.0000	
McFadden R^2	0.2689	
Akaike Information Criterion (AIC)	6451.30	
Number of observations	4000	
Parameters	13	

*Explanatory Notes: * p < 0.1; ** p < 0.05; *** p < 0.01.*

6. Conclusion

In this study, choice data on sweet potato varietal attributes was used to investigate whether respondents consider all the attributes presented when making their choice decisions. Past studies posit evidence that there may be a considerable proportion of respondents who ignore certain attributes in their choice decisions. From this study, it is evident that this is the case from self-reported and also inferred attribute non-attendance. Data analysis has shown that only about 21.3% of respondents reported that they considered all the attributes in their decision making process. Considering ANA in the choice decisions of the respondents resulted in considerable improvement in model fit. Mixed logit models that accounted for both ANA as well as heterogeneity in preferences provided the best model fit to the data.

Moreover, the self-reported ANA was compared to inferred ANA by estimating equality constrained latent class (ECLC) models and the models results confirm previous suggestions by the scientific community that there is a poor mapping between stated and inferred non-attendance. Of particular interest is that respondents stated much higher levels of non-attendance in the supplementary questions, compared to the level of ANA inferred by the ELCL model. The mismatch between stated and inferred ANA values could be explained by endogeneity issues in follow-up questions where respondents are informed that they should actually have considered all attributes. The ECLC model predicted that about 2.1% of respondents attended to all attributes. It was also evident that a lot of respondents ignored the flesh colour attribute, which implies that the attribute may not be a relevant indicator of farmers' preferences in sweet potato varietal improvements. Another issue of concern in the self-reported attendance is that a large proportion of respondents ignored the price attribute. While this was down played in the ECLC model through the predicted probability of 6.1%, it means that for a large proportion of respondents, it would be problematic to estimate the willingness to pay values since these respondents did not consider the trade-offs between changes in price and changes in the sweet potato varietal attributes.

Despite the fact that some respondents ignored certain attributes in their choice decisions, limited knowledge still exists on the reasons for attribute non-attendance. As Hensher et al. (2005) note, there are numerous reasons that can make a respondents ignore attributes, including behavioural irrelevance of an attribute. For this reason, a clear and better understanding of how respondents process attributes and why they would ignore attributes may help to improve the choice set design and the specification of choice models that account for different processing strategies. One way to elicit reasons for non-attendance is to add supplementary questions and to investigate how respondents' and survey characteristics influence ANA. The other approach that can help to explore attribute non-attendance further could be the use of laboratory experiments. This would particularly be useful since results from laboratory experiments can be used to corroborate findings from discrete choice experiments on the way respondents' process different attributes in different choice settings.

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