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Understanding pastoralists' preferences for goat traits: Application of all-levels and end-point choice experiments

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ABSTRACT

Pastoralists are generally known for carefully selecting and maintaining their livestock. In this study, we examine the preferences of pastoralists for goat traits. We employ discrete choice experiments of all levels and endpoints to investigate the relative weights that pastoralists in southern Ethiopia attach to the different traits of does and bucks. Based on data generated from 600 pastoral households, we estimated willingness to pay, trait preference heterogeneity, and attribute nonattendance using different specifications of the mixed logit model. Empirical analysis showed that the all-level design explains the choice strategies of the respondents better than the end-point design. Pastoralists are most interested in tolerance to heat/drought, white coat color, and tolerance to disease both for does and bucks with slightly different orders. The consistency of the relative preferences for the different traits shows that pastoralists are well aware of the different attributes of their animals and have a clear hierarchy of the attributes in choosing the next generation of bucks and does. Our findings imply that breeds with clear advantages in disease resistance and heat tolerance over local breeds might help pastoralists improve their livelihoods.

1. Introduction

Pastoralists are unique custodians of animal genetic resources that have contributed to a wide variety of breeds of livestock that provide a diverse stream of benefits to the environment, humanity, and its cultural heritage (FAO, 2007). Due to the evolution, they have gone through harsh environmental conditions, cattle breeds kept by pastoralists represent reservoirs of genetic diversity and retain many genetic traits, such as fertility, vitality and resistance to diseases and drought, that no longer exist in animals kept in industrial systems (Homewood & Rodgers, 1984; Notenbaert et al., 2012). Embedding the preferences of livestock keepers for the different characteristics of the livestock – which apparently reflect the objectives for which they are being kept - would help design improvement and conservation strategies for sustainable pastoralism.

Considerable scientific effort has been exerted to improve the production and productivity of livestock through various institutional and production innovations (Coppock, 1994; Desta & Coppock, 2004). However, the performance of the livestock sector in general and those of the pastoral and agro-pastoral areas remains considerably low (Kosgey et al., 2008). The constraints that are responsible for the low level of performance of the sector include drought, pests and diseases, lack of food, lack of institutional support, social conflicts, and misguided policy interventions such as changing pastoral areas to commercial farms (Coppock, 1994; Desta, 2011).

Although they are known for their adaptability and resilience, in Ethiopia, and many other eastern African countries, the productivity per unit of animal of the local livestock breeds in pastoral areas is low in absolute terms (Zonabend et al., 2013; Fratkin, 2001; E. Ouma et al., 2007; Muigai et al., 2018). Therefore, a series of research and development investments have been made to develop and/or introduce exotic breeds with higher traction power, milk yield, and beef (Emily. Ouma et al., 2007; Omondi et al., 2008; Kassie et al., 2009). Over the last five decades, exotic breeds and genes from livestock have been imported into the country for research purposes. The exotic breeds were distributed mainly in the middle and highlands of the country. However, the level of

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uptake of 'improved' breeds was found to be negligible (Kassie et al., 2009). The main reason for the very low level of adoption was revealed to be a disconnect between the traits for which the exotic breeds were selected and the traits in which livestock keepers are interested (Emily. Ouma et al., 2007; Scarpa et al., 2003).

Like any other technology, interest in and adoption of new livestock breeds depends on the relative expected utility of the new breeds compared to the ones that livestock keepers already have. This expected utility is defined in terms of the different services or traits the new breeds have compared to the local or already adopted breeds. Therefore, the relative interest of the livestock owners in the attributes of the new breeds is the key determinant of the adoption of the breeds. Consequently, there are several studies that have analyzed the preferences of livestock traits in rural Ethiopia (Emily. Ouma et al., 2007; Omondi et al., 2008; Kassie et al., 2009; Zander & Drucker, 2008; Terfa et al., 2013; Woldu et al., 2016).

In this study, we focus on goats, because they are the most versatile and dominant species of livestock in the pastoral and agro-pastoral livelihood systems of Ethiopia. Ethiopia had a total goat population of 34 million in 2019 (FAO, 2021). The goat population is mainly of local breeds and the level of exotic blood in the goat population is very low (Ayalew et al., 2003).

The disconnect between the public genetic improvement program and farmers' interest is clear, as documented in the few available research reports. The skewed focus of public investments on the meat and milk traits of small ruminants is hardly in line with the traits of interest to the livestock keepers. Based on a stated preference study conducted in Marsabit district of Kenya, (Omondi et al., 2008) reported that disease resistance, body size and conformation, and fertility are the most preferred traits of does, and disease tolerance, drought tolerance, and body size and conformation are the three most important traits of bucks for goat keepers. Using ranking as a mechanism for eliciting preferences, (Misbah, Belay, & Haile, 2015) indicated that milk production, drought tolerance, and fertility were the three most important traits of does, while body size and conformation and white coat color were for bucks in the Afar region of Ethiopia, where pastoralism is the way of life. Using choice experiments, (Woldu et al., 2016) reported that for does, disease tolerance, milk yield, and fertility, and for bucks, body size, and conformation, libido, and disease tolerance were the three most important traits in arid and semi-arid pastoral systems.

Only two of the studies discussed above, (Omondi et al., 2008) and (Woldu et al., 2016), employed behaviorally plausible discrete choice experiments to elicit trait preferences (Louviere, Hensher, Swait, & Adamowicz, 2000; Williams et al., 1998). Choice experiments are stated preference data collection techniques that enable indirect comparison of different attributes of quality differentiated goods/services and estimation of trade-off between the traits being considered. In eliciting preference for traits of animal breeds, hypothetical and multi-attribute animal profiles [alternatives] are experimentally generated, and two or more profiles are combined with or without an opt-out alternative to form a choice set. Then, one or more choice sets are presented to each respondent so that he/she chooses the alternative in the choice set that he/she prefers most. Compared to other common stated preference methods, such as contingent valuation and conjoint ranking or rating, DCEs are theoretically well-founded, behaviorally more relevant, and empirically more reliable (Louviere, Hensher, Swait, & Adamowicz, 2000; Louviere et al., 2010). On the other hand, experimental auctions can be used to capture revealed preferences for products and attributes that can be exchanged in the market (Huffman & McCluskey, 2017; Lusk & Shogren, 2007). Given the nature of our experiment and the objectives of our study, auctions were not appropriate as none of the traits is explicitly transacted on the revealed market. Therefore, we opt for discrete choice experiments (DCEs).

The designing process in DCEs is critical and detailed. One of the critical issues that needs to be addressed in the design process is the attributes and attribute levels that need to be included in the design (Hensher, Rose, & Greene, 2015; Mariel et al., 2021; Scarpa & Rose, 2008; Street & Viney). The quality of the information generated by studies using discrete choice experiments depends on the rigor with which the attributes and their levels are defined (Abiiro, Leppert, & Mbera, 2014). The definition of attributes and their levels requires a thorough understanding of the goods and services to be valued. However, background information is usually not available on non-traded goods and services, particularly in developing countries (Mangham et al., 2009). Every context has its own unique features, and hence there is no universally applicable gold standard for defining attributes and their levels for the discrete choice experiment (DCE). However, common good practices are recommended for the definition of attributes and attribute levels (Kløjgaard et al., 2012).

Levels must be relevant and easy to understand and should have a scope or range that captures and ensures trade-offs between attributes while remaining acceptable to the respondent (Green & Srinivasan, 1978). This is important because the level range affects the estimates derived from the design (Kløjgaard et al., 2012; Green, 1974). These intricacies imply the rigor required in determining the levels of the attributes in a choice experiment.

Holmes et al. (2017) indicated that although the definition of attributes and their levels are critical to the successful implementation of CE, it is often not given due consideration. To our knowledge, there is no study that compares designs of similar attributes but different attribute levels. Therefore, we are digressing from the common practice of using one design for our choice experiment. We developed two designs with different combinations of attribute levels to investigate whether differences in design will result in different implicit prices for traits. The first design is formulated based on all attribute levels defined by the pastoralists. The other design is based only on the extreme (minimum and maximum) levels of the traits. Using extreme values for all attributes will result in a design commonly called the endpoint design [hereafter referred to as EP], and a design designed with all levels is called the all-level design [hereafter referred to as AL].

Therefore, this study will contribute to the relevant body of knowledge in at least two ways. First, it presents empirical evidence on how the utility weights of attributes would be affected when non-border trait levels are excluded from the description of the alternatives. Second, we will show whether the quality of the estimator varies between the two designs or simply whether the end-point-level designs are good enough.

We conducted our study in Konso and Yabello areas of southern Ethiopia. These are locations where livestock are the pillar of the agro-pastoral livelihood system. Goats are the second most important livestock after cattle, both in number and in economic contribution. Despite the continued effort to introduce exotic blood into the goat population, it is quite clear that the population is entirely indigenous (Mekuriaw & Harris-Coble, 2021).

Our study, therefore, intends to contribute to the elicitation of the trait preferences of pastoral and agro-pastoral communities in southern Ethiopia in order to provide valuable information on the interests of the target communities for livestock breeders. Our study addresses this key question with two separate designs, that is, EP and AL. The series of random parameter logit models estimated on the EP and AL designs data show that respondents are most interested in heat/drought tolerance, white coat color, and disease tolerance both for does and bucks with slightly different orders.

Recent empirical studies on choice modeling have shown that respondents usually follow simple decision rules or 'heuristics' that result in nonattendance to certain attributes (ANA), and that failure to account for attribute nonattendance (ANA) may lead to biased coefficient and WTP estimates (Hensher & Rose, 2009; Scarpa et al., 2010; Campbell et al., 2011; Caputo et al., 2016). In the analysis, we account for ANA to increase the understanding on the attribute processing strategies of the respondents by observing whether they ignore information provided in choice sets.

The remainder of this paper is structured as follows. Next, we present the methodology we followed including the sampling procedure, choice experiment survey, and analytical framework. Then, we discuss the willingness to pay, preference heterogeneity, and attribute nonattendance results. Finally, we present the conclusion and key implications of the study.

2. Methodology

2.1. Study location and samples

The study covered two purposively selected districts in southern Ethiopia, namely Konso and Yabello districts. The main criterion for the selection of the two districts was the importance of the livelihoods of pastoralists and agropastoralists and the role that goats play in the rural economy. Konso is a district in southern Ethiopia located about 590 km south of Addis Ababa, the national capital. The district has an estimated area of 2354 km^2 and is divided into 44 peasant associations and 2 towns. The last national census in 2007 reported that the district had a population of 235,000 (CSA Central Statistical Authority, 2010). Agro-pastoralism is the mainstay of life where subsistence-oriented crop and livestock production sustain livelihoods. The semi-arid lowland areas support the majority – about two-thirds - of the population, and agricultural uplands in the middle altitude support the rest of the primarily cultivating population.

Yabello is one of the 13 pastoral districts in the Borana Zone, in southern Ethiopia, located to the east of Konso about 570 km from Addis Ababa. According to the 2007 census, the Yabello district had a population of 102,000 (CSA Central Statistical Authority, 2010). The landscape of Yabello is dominated by plain bushlands. According to Coppock (Coppock, 1994), Yebello's landscape is gently undulating across an elevation of 1450–1600 m above sea level and it entirely falls within the Great Rift Valley System of East Africa. The main economic activity in Yabello is livestock production, with crop production growing in importance due to the growing influence of the government to settle pastoralists for a sedentary life.

In each district, we randomly identified three livestock markets. In Konso, we selected Jarso, Mesoya, and Dera weekly markets out of the five livestock markets in the district. Jarso and Mesoya happened to be the two largest, while Dera was the smallest market in the district. In Yabello, we selected the weekly Darito, Eleweya, and Dubluq markets out of the six markets in the district. Dubluk was the second, Eleweya the third, and Darito was the sixth market in terms of size. In each market, we talked to 100 respondents, and hence a total sample size of 600 livestock keepers. Respondents were systematically selected, so that all other people coming to the market were included in the sample. The survey in each market was completed over two days in the market that spanned more than a week. The survey was carried out between November and December 2017.

2.2. Choice experiment

The design of the choice experiment began with a detailed discussion with agro-pastoralists and animal breeders on the traits considered important in the identification of goats for production and marketing performance. Based on the discussions and published literature (Omondi et al., 2008; Woldu et al., 2016), ten traits were initially considered – including the type of horn and the fertility / birth interval – for an average-aged buck and doe. The average age of a buck is 2.5 years, and it is 2 years for does. Finally, pairwise ranking of the traits was conducted with livestock keepers and the final list of traits was determined. The traits considered for bucks were body size, kid vigor, disease tolerance, heat tolerance, and coat color. For does, we considered milk / day, kid vigor, disease tolerance, heat tolerance, coat color, and price/head (Table 1).

Body size refers to the weight [gauged by eyeball evaluation] and the condition of the animal. Milk yield is the quantity of milk harvested in cups per day per doe, while the goat is lactating. Kid vigor implies the energy and strength of the child in the first few days after birth. vigor also indicates the strength and adaptability of the child to the harsh environment in which it is growing. Tolerance to disease implies the ability of the animal to withstand the different parasites and diseases that are common in the area, such as ticks and trypanosomiasis. The animal's ability to survive and thrive in the presence of this and other diseases was the definition of disease tolerance adopted in the choice experiment.

Table 1
Traits and trait levels considered in the choice experiment.

	Bucks Design1	Design 2	Does Design1	Design 2
Trait	All levels	End points	All levels	End points
Body size	Small Medium Big	Small Big		
Milk/day			1 Cup (0.25 liter) 2 Cup (0.50 liter) 3 Cup (0.75 liter)	1 Cup (0.25 liter) 3 Cup (0.75 liter)
Kid vigor	Weak Medium Strong	Weak Strong	Weak Medium Strong	Weak Strong
Disease tolerance	Low Medium Good	Low Good	Low Medium Good	Low Good
Heat tolerance	Low Medium Good	Low Good	Low Medium Good	Low Good
Coat color	Black Mixed White	Black White	Black Mixed White	Black White
Price/head[$]	1200 1600 2000 2400	1200 1600 2000 2400	700 1000 1300 1600	700 1000 1300 1600

[$] Price is in Birr. Birr the official currency of Ethiopia and was equivalent to US $ 0.0386 in October 2017.

On the other hand, heat / drought tolerance means the goat's ability to withstand thirst that happens due to the strong sun light and the lack of water resources in the grazing areas. Animals that are heat tolerant are the ones that will be able to survive in harsh environments, and therefore, it is an important trait farmers consider in identifying or selecting the animals to keep. The coat color implies the dominant color of the animal's fur. A dominant color was defined as the one that covered more than 75% of the animal's body. The mixed color implied a color where the combination was not dominated by any single color. The price ranges were determined considering seasonal and market variations over a one-year period, that is, between October 2016 and October 2017.

We considered trait preferences for bucks and does separately. Two choice experiments were designed for bucks and two others for does, based on the different trait levels. One design considered all potential levels of the identified traits, while the other considered only the end levels [extreme values] of the traits.

The four designs were generated using Ngene (ChoiceMetrics, 2018). All variables were effects coded and assumed to be positive and normally distributed. Initial values of the parameters were generated from the relevant literature and used as priors in the design process. The designs generated 24 profiles each, and two profiles were put experimentally together to form the choice sets. We use a constrained design to avoid dominant and dominated alternatives. The number of alternatives in all choice sets was three (the two profiles and an opt-out option) and the only difference between the two designs was whether the goat profiles were described with all levels or only end levels of the traits. The

Bayesian efficient designs have very low D-errors (See Table A1 in the appendix).

The designs and choice cards were randomly assigned to the respondents and the enumerators to minimize measurement error. Choice situations from each of the four designs were presented to 150 respondents, resulting in 5400 (= 150*12*3) rows of data per design. Each respondent was presented with 12 choice cards from only one of the four designs. The cards were presented to each of the respondents in random order. Each enumerator was given 12 choice cards from one design in the morning, and these cards will be replaced with other 12 from another design in the afternoon. This arrangement was followed throughout the survey.

The respondents were first briefed about the objectives of the study, the mechanics of preference elicitation, and asked if they would agree to participate in the survey. Once their verbal consent was acquired, 2 or 3 cards were randomly selected, and pilot choice experiments were carried out to ensure that they had understood the process. To account for the illiteracy of the respondents, pictorial representations of the traits and trait levels were carefully designed on the choice cards (Fig. 1) and interviews were conducted in local vernaculars.

2.3. Analytical framework

Random parameters logit in willingness to pay (WTP) space

The choices of decision makers among mutually exclusive alternatives in a given choice situation can be explained using discrete choice models (Louviere, Hensher, Swait, & Adamowicz, 2000; Williams et al., 1998; Alpizar et al., 2003). Decision makers in this study are pastoralists, and the alternatives represent hypothetical goat profiles characterized by varying traits and trait levels. Based on the characteristic's theory of value (Lancaster, 1966) and the random utility theory (McFadden, 1974), the probability of choosing alternative i, $P(i)$, in a given choice situation (C_t), is equivalent to the probability that the expected utility (U), from alternative i is greater than the expected utility from other alternatives within the choice situation. In the two-alternative (i *and* j) case, this can be written for an individual n as:

$$P(i|C_{nt}) = P(\ U_{nit} > U_{njt}),\ \forall\ i \neq j \tag{1}$$

The utility function is expressed as a function of deterministic and unobserved factors. Following Train (1999) and (Train & Weeks, 2005), we assume that the utility function is linear in the explanatory variables and utility is separable in price, p, and a vector of nonprice traits characterizing the alternatives and a dummy variable for the alternative specific constant (ASC), x_{njt}. So, we write the utility function as:

$$U_{nit} = -\alpha_n p_{njt} + \beta_n^{'} x_{njt} + \epsilon_{njt} \tag{2}$$

where α_n and β_n are pastoralist specific coefficients and ϵ_{njt} is Gumbel distributed with mean zero and variance of $\sigma_n^2\left(\frac{\Pi^2}{6}\right)$, where σ_n is an individual scale parameter. There exists an infinite set of combinations of values for the pastoralist specific coefficients and scale parameter, and hence model (2) above is not identified. Normalizing Eq. (2) helps to make it identifiable, and this can be done in many ways (Train & Weeks, 2005). One of the options is dividing Eq. (2) by σ_n. Normalizing the utility function can be done in many ways (Train & Weeks, 2005). This normalization will not affect the behavior of the models and results in a new error term that is independently and identically distributed (iid) extreme value type I with variance equal to $\frac{\Pi^2}{6}$ (Train & Weeks, 2005; Scarpa et al., 2008). The division results in the following.

$$U_{nit} = -(\alpha_n\,/\,\sigma_n)p_{njt} + (\beta_n/\sigma_n)^{'} x_{njt} + \epsilon_{njt}/\sigma_n \tag{3}$$

The utility coefficients are defined as $\lambda_n = \alpha_n/\sigma_n$ and $c_n = \beta_n/\sigma_n$, and $\zeta_{njt} = \epsilon_{njt}/\sigma_n$ such that the utility model in preference space is written as:

$$U_{njt} = -\lambda_n P_{njt} + c_n^{'} x_{njt} + \zeta_{njt} \tag{4}$$

It is also important to note that the random error term in Eq. (2) is different from the derived one in Eq. (4) below. As originally presented by Train and Weeks (Train & Weeks, 2005) and (Scarpa et al., 2008), the error term in Eq. (2) is Gumbel iid, with mean zero and variance $\sigma^2\left(\frac{\pi^2}{6}\right)$, whereas the one in Eq. (4) is Gumbel iid, with mean zero and variance $\frac{\pi^2}{6}$.

We estimate the coefficients of the utility function using the random parameter logit (RPL) model, which is a flexible model that avoids the limitations of the conditional logit model by allowing for random taste variation, unrestricted substitution patterns, and correlation in unobserved factors overtime (McFadden & Train, 2000; Train, 2003). The utility coefficients (c_n) represent the marginal utility pastoralist n derives from changes in nonprice traits of bucks and does. Similarly, λ_n represents the marginal utility pastoralist 'n' derives from reductions in prices of bucks and does. The ASC captures the utility that pastoralists derive from choosing hypothetical goat profiles instead of opting out. The analysis started with different versions of heterogeneity in mean RPL model in the preference space. These estimations were intended to investigate the heterogeneity around the average preference for the traits.

We are also interested in estimating and comparing willingness-to-pay (WTP) values for the traits between the two designs. The WTP values are the ratios of two randomly distributed coefficients. Depending on the choice of distributions for the random coefficients, this can lead to WTP distributions that are heavily skewed and may not even have defined moments (Train & Weeks, 2005; Scarpa et al., 2008). This problem has led to the estimation of RPL in willingness to pay space (Train & Weeks, 2005; Scarpa et al., 2008). This involves estimating the distribution of willingness to pay directly by reformulating the model in such a way that the coefficients represent the WTP measures (Hole & Kolstad, 2012). Therefore, we have estimated RPL models in WTP space to show the relative importance of the traits from the perspective of agro-pastoralists.

The WTP for a goat trait is the ratio of the trait's coefficient to the goat price coefficient, i.e., $w_n = \frac{c_n}{\lambda_n}$. This definition allows us to write the utility function in WTP space as[1]:

$$U_{njt} = -\lambda_n P_{njt} + (\lambda_n w_n)^{'} x_{njt} + \zeta_{njt}. \tag{5}$$

Scarpa et al. (2008) recommend that the correlation or interdependence of the estimated WTP values needs to be estimated whenever the data allow it. Hess and Train Hess and Train (2017) also emphasize that the random coefficients of the RPL could be correlated for many reasons that could induce related preferences for the traits considered. Hence, they pointed out that a RPL model, both in preference and in WTP spaces, with full covariance among coefficients includes all sources of correlation, including the correlation that is induced by scale heterogeneity. Therefore, we have estimated and presented RPL models with fully correlated WTP values.

Latent Class Modelling – Attribute Nonattendance

Another important dimension of the preference analysis that we examined is the choice simplification strategy of respondents. Respondents employ different strategies to simplify the process of comparing and choosing the alternative in each choice set. Attribute nonattendance (ANA) - ignoring one or more of the traits - is one of the most observed strategies [also known as heuristics] in the application of discrete choice experiments to elicit quality differentiated goods and services (Lagarde, 2013; Scarpa et al., 2009). Hensher, Rose, & Greene

[1] This is another normalization of equation (2), where the unit free utility function is divided by the coefficient of price and multiplied by the ratio of coefficient price and the scale parameter. The error term in equation (5) has the same properties with the one in equation (4).

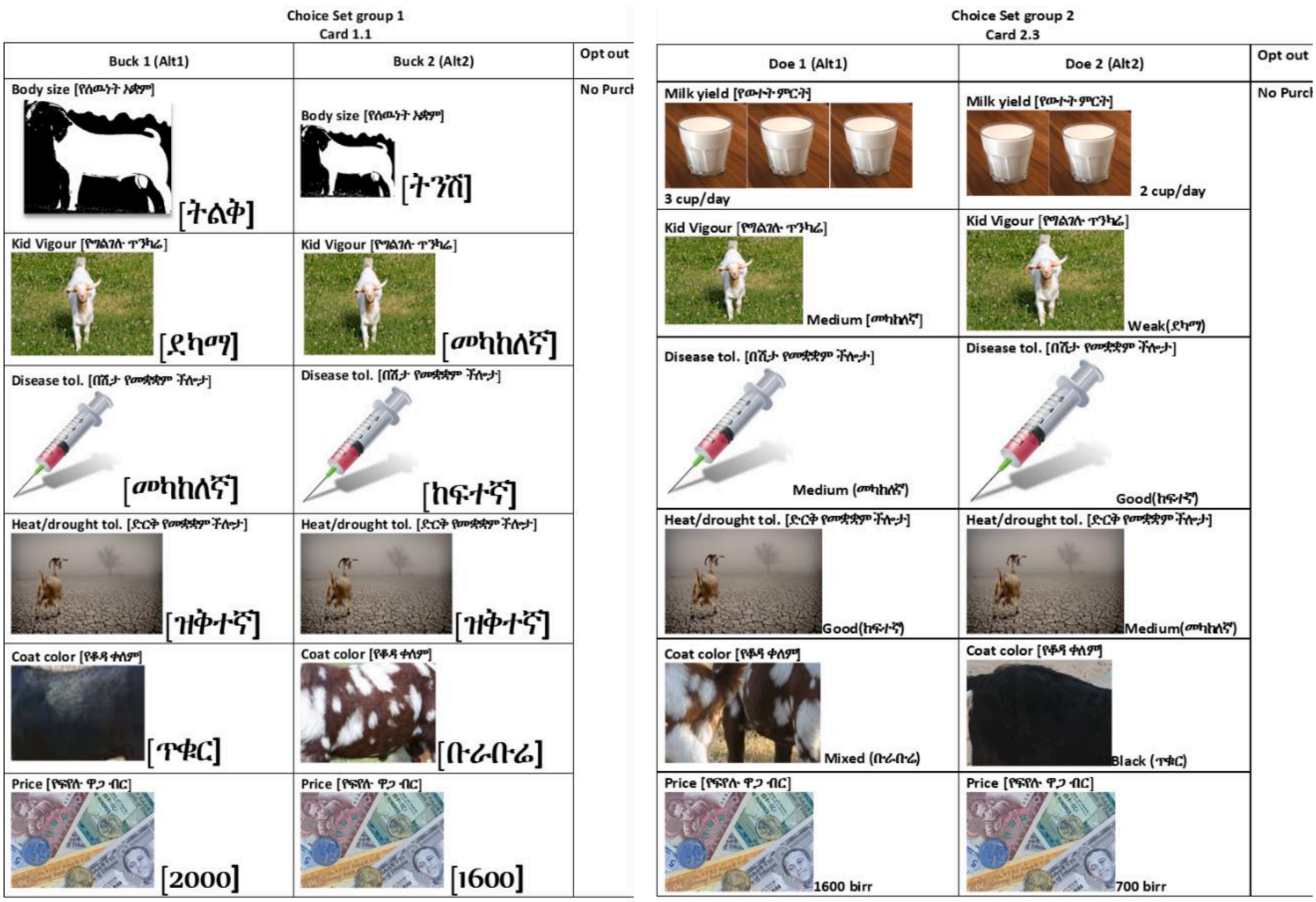

Fig. 1. Sample choice cards of the choice experiment.

(2015) emphasize that 'whatever the drivers that influence the behavioral response in the stated choice studies, be they inherent in the way respondents think and believe, and/or in the inducement of structural elements of the choice experiment, ANA is a real phenomenon in general.'

Therefore, we analyzed ANA at the levels of traits considered to ensure that the simplification strategies of respondents are fully captured (Caputo et al., 2016; Erdem et al., 2015). ANA can be captured either by asking respondents to indicate the attributes they ignored, or can be inferred based on the relative weights of the random coefficients of the utility model. We did not generate data on stated non-attendance, and hence we will be reporting results only from inferred ANA.

We estimate a series of latent class models to investigate patterns of ANA. The latent class model is a type of mixed multinomial logit model, when the mixing density function of the coefficients to be estimated, $f(\beta)$, is of discrete nature – with β taking a finite set of distinct values (Train, 2003; Goodman, 1974; Vermunt & Magidson, 2007). If we assume that β takes M possible values labeled $b_1, \ldots, b_M$, with probability s_m that $\beta = b_m$, the mixed logit becomes the latent class model. The choice probability is therefore given as

$$P_{nit} = \Sigma_{m=1}^{M} s_m \left(\frac{e^{b_m' x_{nit}}}{\Sigma_j e^{b_m' x_{njt}}} \right) \tag{6}$$

As Train (2003) indicated, this specification is useful 'if there are M segments in the population, each of which has its own choice behavior or preferences'. The share of the population in segment m is s_m, which can be estimated within the model along with the b's for each segment. In our case, each segment denotes the proportion of sampled households with similar ANA patterns. Following (Hensher et al., 2011), we constrain the estimates of parameters for each trait between classes to be the same, since we are interested in a single choice that conditions the outcome on the inferred attribute nonattendance rules. Following (Campbell et al., 2011) and (Caputo et al., 2016), our analysis considers ANA at the level of trait levels, as the comparison of two designs requires specifying the models with the different levels of the traits included in the utility model. We follow the methodology suggested by Scarpa et al. (2009); Campbell et al. (2011), and (Lagarde, 2013) in gradually estimating the latent class models with constraints on the coefficients of the traits and/or trait levels assumed to be ignored at every step.

3. Results and discussion

3.1. Sample population

Most (88%) of our sample respondents were household heads and 67% of them were male. The average literacy of the household heads is only 1.7 years of education. Literacy includes both formal and informal (e.g., religious) education and hence reaches up to 35 years among sample respondents. The average respondent was 39.3 years old, was from a family of seven that owned 15 sheep and 46 goats. The respondents visited the livestock market on average 4 times in a year and walked almost 2 h to get to the market (Table 2). These are remote agro-pastoral areas where access to markets, like many other social services, is very limited. In fact, the agro-pastoral production system in southern Ethiopia is subsistence oriented with little dependence on the market. Therefore, the low average market visit per year is not unexpected.

Table 2
Characteristics of the respondents.

	Mean/Freq. (%)	Min	Max	Std. Dev.
Gender of respondent				
Female	33			
Male	67			
Respondent is HH head (Yes)	88			
Respondent is (agro-) pastoralist (Yes)	95.17			
HH owns livestock (Yes)	97.17			
Age in years	39.31	17	98	15.40
Literacy (in years of education)	1.69	0	35	3.22
Household (HH) size	6.77	1	19	2.71
Number of females in the HH	3.32	0	10	1.63
Number of males in the HH	3.44	0	13	1.78
Farm size (in hectares)	4.01	0	60	3.70
Number of adult sheep	10.49	0	200	19.81
Number of lambs	4.43	0	111	10.01
Number of adult goats	34.39	0	310	49.18
Number of kids	11.39	0	160	17.76
Distance to market (in hours)	1.94	0	12	1.44
Frequency of market visit in/year	4.42	0	96	7.59
Observation	600	600	600	600

Note: Freq. stands for frequency, Min. stands for minimum, Max. stands for maximum, and Std. dev. Stands for standard deviation.

Agro-pastoralism is the mainstay of most (95%) of our sample respondents, and more than 97% of them owned livestock. The number of goats owned by households is much higher than that of sheep, and this is expected, given the arid nature of the pastoral areas where goats naturally thrive more than sheep.

3.2. Willingness to pay for buck and doe traits

While there is considerable difference in the number of parameters estimated, model goodness of fit criteria tend to favor the EP design-based models for bucks and the AL design-based models for does. Despite the values of the criteria, the WTP space estimation of the AL design-based RPL for does was not meaningful as price was not statistically significant. Price happens to be insignificant whenever its levels are below what is currently existing in the market or when respondents ignore it as part of their simplification strategy (discussed below in Section 3.4) (Carlsson et al., 2010; Sever, Verbič, & Sever, 2019). All models, except the AL DCE based RPL for doe traits, have resulted in positive and significant alternative specific constant (optout = 0), implying that agro-pastoralists prefer selecting one of the "purchase" alternatives rather than opting out, all else being equal.

In estimating the WTP for buck traits, the EP design-based estimations resulted in expected and meaningful values compared to the AL design-based estimations. The WTP values estimated in the EP design show that livestock keepers are willing to pay US$ 85.3 for high heat/drought tolerance, US$ 48.7 for white (cf. black) coat color, US$ 45 for high (cf. low) disease tolerance and US$ 23.33 for good (cf. poor) kid vigor in bucks (model 1.2 Table 3). Considering the AL design, livestock keepers are willing to pay US$ 39.3 for high (cf. low) heat/drought tolerance, US$ 31.7 for white (cf. black) coat color, US$ 28.3 for medium (cf. low) heat tolerance and US$ 25.67 for medium (cf. low) disease tolerance in bucks (model 1.1 Table 3). Estimations based on the two designs similarly ranked drought tolerance, white coat, and disease tolerance as the three most important traits of bucks. However, it is clear that the marginal WTP values derived from the EP design are larger than those of the AL design.

For the does, the model on the EP design data shows that heat/drought tolerance, disease tolerance, and white coat are the most important traits. This ranking is almost the same as that of the buck traits, except the white color is less important than the disease tolerance in the case of does (see models 1.2 and 2.2 in Table 3). The respondents are willing to pay US$ 66 for high (cf. low) heat/drought tolerance, US $47.7 for high (cf. low) disease tolerance, US$33.7 for white (cf. black) coat color, and US$ 17.33 for good (cf. poor) kid vigor in does (model 2.2 Table 3).

Considering both the designs and the animals, goat keepers have consistently shown the highest interest in the heat / drought tolerance

Table 3
Willingness to pay for goat traits with full covariance matrix.

	(Model 1.1) Buck all levels	(Model 2.1) Doe all levels	(Model 1.2) Buck end points	(Model 2.2) Doe end points
Coefficient Mean				
Constant (optout=0)	9.82***	66.23	22.40***	9.83***
	(1.95)	(245.28)	(6.08)	(2.52)
Body size (Big) [BSZ]	0.44			
	(0.27)			
Body Size (Medium)	−0.77		0.04	
[MSZ]	(0.77)		(0.23)	
Kid vigor (Strong)	0.07	1.31	0.70***	0.52***
[KVS]	(0.34)	(4.83)	(0.19)	(0.17)
Kid vigor (Medium)	0.10	−0.71		
[KVM]	(0.18)	(3.53)		
Disease tolerance	0.08	9.27	1.35***	1.43***
(High) [HDST]	(0.96)	(33.85)	(0.41)	(0.39)
Disease tolerance	0.77**	12.16		
(Medium) [MDST]	(0.36)	(47.09)		
Heat tolerance (High)	1.18**	19.28	2.56***	1.98***
[HDRT]	(0.60)	(73.24)	(0.59)	(0.49)
Heat tolerance	0.85***	7.58		
(Medium) [MDRT]	(0.27)	(28.48)		
Coat color (Mixed)	0.03	5.64		
[MXC]	(0.18)	(21.56)		
Coat color (White)	0.95**	1.93	1.46***	1.01***
[WCL]	(0.37)	(7.27)	(0.37)	(0.31)
Milk (liter) [MLK]		7.80		0.14
		(30.80)		(0.15)
Price of goat (,000	−0.69***	−3.15	−1.37***	−1.03***
Birr) [FEE]	(0.24)	(3.79)	(0.24)	(0.26)
Coefficient standard deviation (Unobserved heterogeneity in mean)				
Body size (Big) [BSZ]	0.717***		0.033**	
	(0.273)		(0.226)	
Body Size (Medium)	1.637***			
[MSZ]	(0.610)			
Kid vigor (Strong)	0.930***	11.269	0.231**	0.530***
[KVS]	(0.257)	(43.402)	(0.120)	(0.183)
Kid vigor (Medium)	0.327**	6.281		
[KVM]	(0.152)	(23.801)		
Disease tolerance	1.996***	15.394	0.837***	0.826***
(High) [HDST]	(0.616)	(58.739)	(0.250)	(0.254)
Disease tolerance	0.754**	8.599		
(Medium) [MDST]	(0.312)	(32.919)		
Heat tolerance (High)	1.840***	11.771	1.498***	0.810***
[HDRT]	(0.366)	(44.626)	(0.342)	(0.233)
Heat tolerance	0.813***	9.478		
(Medium) [MDRT]	(0.215)	(36.233)		
Coat color (White)	0.948***	11.224	1.086***	1.052***
[WCL]	(0.234)	(42.582)	(0.246)	(0.289)
Coat color (Mixed)	0.646***	6.569		
[MXC]	(0.155)	(25.503)		
Milk (liter) [MLK]		12.057		0.374*
		(46.204)		(0.158)
Price of goat (,000	1.084***	0.571***	1.020***	0.739***
Birr)	(0.155)	(0.086)	(0.141)	(0.125)
Observations	5400	5400	5400	5400
LL	−1322.40	−1132.96	−1171.86	−1322.50
AIC	2800.80	2397.92	2399.71	2701.00
BIC	3315.14	2833.14	2584.35	2885.64

Note: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. LL stands for log likelihood at convergence. AIC denotes Akaike Information Criterion. The estimation commands and additional results are available upon request from the corresponding author. The models were estimated using the Stata command *mixlogitwtp* written by (Hole, 2016). We assumed all random coefficients to be correlated and used 2000 Halton draws in estimating the models.

trait. This is a finding that differs from previous related studies in Ethiopia (Woldu et al., 2016) and Kenya (Omondi et al., 2008). The dry and hot environment requires the identification and raising of goats that can thrive at high temperatures. Similarly, the white coat color of goats emerged as an important trait that positively affected the choice of buck in these pastoral and agro-pastoral settings. The white coat helps animals reflect the scorching sunlight and therefore reduces their need for water, which is a very scarce resource in these environments. The white coat also helps repel external parasites such as tsetse fly.

Another interesting result is the insignificance or marginal significance of body size as a trait affecting buck choice. Pastoralists usually do not intend to fatten or raise big goats (Omondi et al., 2008). They are rather interested in a higher number of animals both for financial and social (prestige) reasons. The finding of the lack of interest in body size, while showing interest in kid vigor – at least in EP designs – suggests that the preferences of pastoralists are more about the number of animals rather than the meat yield per animal.

3.3. Preference heterogeneity

The WTP values we discussed above are the average implicit prices that the sample households attach to the traits and can be considered as the weights of relative importance. However, the average does not reflect the importance of the trait and/or trait level to each of the respondents. This is because of the heterogeneity in preferences from one individual to another. Estimates of random parameter logit (RPL) models in WTP spaces (Section 3.1 above) revealed the presence of unobserved preference heterogeneity (Coefficient standard deviation panel of Table 3 above). Therefore, we estimated a set of RPL models to explain the unobserved behavior with some socioeconomic characteristics that are theoretically and contextually related to consumption behavior.

The gender of the respondent was considered to test the hypothesis that male and female respondents have different tastes for the traits/trait levels. Literacy level (in years of education), goat and sheep herd size (in tropical livestock units), household size, and market access (in walking distance) were also considered to see if these characteristics have any influence on the goat trait preferences of the respondents. The models were estimated in two stages. First, we estimated a RPL model with mean heterogeneity, with full interaction between the socioeconomic variables and all traits with 100 Halton draws. Once the specification search was completed, we retained the significant interactions and estimated the models with 500 Halton draws.

The heterogeneity in mean models for bucks show that the parsimonious EP DCE based models have better goodness of fit. However, the explanation of the heterogeneity is more meaningful in the AL DCE-based model. The detailed modeling of the levels of the attributes gives a better insight into the difference in tastes for traits among respondents.

The socioeconomic variables included in the model estimated in the DCE AL buck trait explained, at least partially, the heterogeneity around the mean taste parameters (Model 1 in Table 4). The sex of the respondents was the most important variable in explaining the unobserved heterogeneity around the average taste parameters for the traits. The female respondents had a significantly higher interest in medium body size and medium tolerance to drought compared to the male respondents. On the other hand, male respondents have shown a significantly higher interest in large and medium body size, good child vigor, high tolerance to disease and high and medium tolerance to drought (model 1 Table 4). The distance from the livestock markets in walking hours and household size also explain the preference heterogeneity around the white coat of bucks. As household size increases, the interest in white-coated bucks increases. This is related to minimizing the risk of trypanosomiasis transmitted by the tsetse fly, a vector that prefers darker colors in selecting its victims (Kassie et al., 2009).

The socioeconomic variables considered in the heterogeneity model based on the EP design for bucks did not reveal much variations in preferences (model 2 Table 4). Only the distance from the livestock markets in walking hours was found to explain part of the unobserved heterogeneity around the mean taste parameter for the high tolerance to drought in bucks. The farther the respondent is from the livestock market, the less interested he or she is in drought of the bucks. This is probably because the vegetation cover increases with increasing

Table 4
Heterogeneity in mean RPL models for buck traits: all-level and end-point designs.

	Model 1 Coeff.	St. error	Model 2 Coeff.	St. error
Coefficient mean				
Random parameters in utility functions				
Body size (Big) [BSZ]	0.098	0.231	0.018	0.087
Body Size (Medium) [MSZ]	0.010	0.094		
Kid vigor (Strong) [KVS]	.289***	0.110	.225***	0.042
Kid vigor (Medium) [KVM]	0.067	0.089		
Disease tolerance (High) [HDST]	.564*	0.289	.411***	0.1
Disease tolerance (Medium) [MDST]	0.140	0.109		
Heat tolerance (High) [HDRT]	.731***	0.184	.888***	0.109
Heat tolerance (Medium) [MDRT]	.252***	0.079		
Coat color (Mixed) [MXC]	−0.030	0.068		
Coat color (White) [WCL]	0.000	0.233	.497***	0.069
Price of goat (,000 Birr) [FEE]	−0.571***	0.117	−0.431***	0.096
Non-random parameters in utility functions				
Constant (optout = 0)	4.120***	0.302	3.612***	0.24
Observed heterogeneity in mean				
BSZ x Gender	.314***	0.119		
MSZ x Gender	−0.131*	0.075		
KVS x Gender	.142**	0.068		
KVM x Distance to market	−0.052	0.033		
HDST x Gender	.251*	0.135		
HDRT x Gender	.257**	0.128		
HDRT x Distance to market			−0.094**	0.039
MDRT x Gender	−0.132**	0.067		
WCL x Household size	.063**	0.030		
WCL x Distance to market	.120**	0.057		
FEE x Gender			0.084	0.079
Coefficient standard deviation (Unobserved heterogeneity in mean)				
Body size (Big)	.233**	0.102	0.163	0.115
Body Size (Medium)	0.090	0.129		
Kid vigor (Strong)	.265***	0.086	.135*	0.08
Kid vigor (Medium)	0.025	0.100		
Disease tolerance (High)	.406***	0.104	.352***	0.07
Disease tolerance (Medium)	.186*	0.101		
Heat tolerance (High)	.537***	0.090	.498***	0.063
Heat tolerance (Medium)	.285***	0.086		
Coat color (Mixed)	.373***	0.071		
Coat color (White)	.561***	0.102	.562***	0.065
Price of goat (,000 Birr)	.560***	0.086	.547***	0.088
LL		−1340.13		−1154.84
McFadden pseudo R^2		0.322		0.416
AIC		2744.3		2339.7

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. LL stands for log likelihood at convergence. AIC denotes Akaike Information Criterion. The models were estimated using NLOGIT 6. The estimation commands and additional results are available upon request from the corresponding author.

distance from the market areas, which are always located in towns. This might create covers or canopies for the animals while browsing and grazing concomitantly reducing exposure to heat and as a result the demand for heat/drought tolerance.

Otherwise, the heterogeneity in mean RPL model resulted in taste parameters with a relative weight like that in the RPL in WTP space without any socioeconomic variable (Model 2 in Table 4).

The heterogeneity in mean models for does result in comparable patterns, except that the goodness-of-fit criteria favor the AL DCE based models. Estimation based on the AL design shows that socioeconomic variables explain some of the heterogeneity to a greater extent than the one in the EP design (Table 5). As the distance to the livestock market increases in walking hours, interest in high disease tolerance and high drought tolerance tends to increase. This is likely related to limited understanding of the level of disease and drought risk in production systems, which in turn could be due to the lack of advisory services that help inform agro-pastoralists. However, as the distance to the livestock market increases, the concern about the market price decreases (model 1 in Table 5). This is again related to the lack of options, and, therefore, the small ruminant keepers would not mind receiving whatever the market offers.

As the size of the small ruminant herd increases, the interest in high disease tolerance decreases. This might not sound intuitive, and yet, as a major indicator of wealth, large herds imply wealth, and hence lower risk aversion tendencies. However, the herd size is positively related to the preference for white-coated does. This could be for disease resistance purposes as well as for higher marketability of the entire herd, as black-coated livestock usually fetch less price compared to lighter-coated livestock (Kassie et al., 2009). The interest in high resistance to diseases increases with increasing family size. Given the importance of livestock as the mainstay of livelihood in this part of the country, it is expected that large families attach higher importance to tolerance to disease. Households with large herds are also interested in white coat color. As the literacy level increases, the interest in the milk productivity of the doe increases. This could be due to many reasons, including awareness of health, increased interest in consuming a nutritious food in milk, interest in commercial opportunities, and interest in the goat's mothering ability[2](model 1 in Table 5).

The heterogeneity in mean RPL model estimated in the EP design did not explain the unobserved heterogeneity except for around the white coat, as in the case of bucks. Interest in the white color increases as the size of the herd, the size of the household and the distance to the market increase. This relationship is straightforward and intuitive. This model has also shown that as the size of the herd increases, the interest of the respondents in the milk production of the doe decreases (model 2 in Table 5). It can be deduced that pastoralists who want to have many kids also do not expect to produce lot of milk.

The common criteria show that the EP design model fits the data better compared to the AL design for bucks. However, this could simply be due to parsimony. Generally, the AL design-based models enabled us to capture the sources of preference heterogeneity than the EP design-based analysis. Detail modeling of attributes' levels gives a better understanding of the differences in traits preferences between respondents.

3.4. Attribute nonattendance

We estimated a series of latent class models (LCMs) to investigate the attribute/trait non-attendance (ANA) patterns between the two designs. We estimated three models for each of the two designs [AL DCE and EP DCE].

Starting with AL DCE for buck traits, the first model (model 1.1 in Table 6) has 13 classes including classes of full attendance (Class 1) and full nonattendance (Class 2). Class 3 to 13 denoted ignoring one attribute at a time (Table 6). The second model (not reported) had 61 classes, which included classes of full attendance (Class 1), full nonattendance (Class 2), one attribute ignoring classes with size greater than 5% in Model 1, and all two-attribute ignoring classes. The third and final model (Model 1.2 in Table 6 below) has six classes with full attendance (Class 1), full nonattendance (Class 2) still maintained, and those classes with size greater than 5% in the second model.

[2] We appreciate the comments made by one anonymous reviewer of the journal for very useful insights on this.

Table 5
Heterogeneity in RPL mean models for doe traits: all-level and end point designs.

	Model 1 Coeff.	St. error	Model 2 Coeff.	St. error
Coefficient mean				
Random parameters in utility functions				
Kid vigor (Strong) [KVS]	0.029	0.110	.189***	0.053
Kid vigor (Medium) [KVM]	−0.108	0.069		
Disease tolerance (High) [HDST]	0.428	0.280	.596***	0.076
Disease tolerance (Medium) [MDST]	.456*	0.256		
Heat tolerance (High) [HDRT]	.830***	0.235	.873***	0.071
Heat tolerance (Medium) [MDRT]	.260***	0.072		
Coat color (White) [WCL]	0.039	0.124	−0.249	0.181
Coat color (Mixed) [MXC]	.281***	0.072		
Milk (liter) [MLK]	.323***	0.124	.150**	0.061
Price of goat (Birr) [FEE]	−0.239	0.325	−0.63***	0.139
Non-random parameters in utility functions				
Constant (optout = 0)	2.760***	0.488	3.309***	0.228
Observed heterogeneity in mean				
KVS:EDU	0.030	0.020		
HDST x Household size	0.046	0.032		
HDST x Distance to market	−0.182***	0.059		
MDST x Household size	−0.023	0.029		
MDST x Distance to market	0.081	0.052		
HDRT x Small ruminant herd size	−0.015*	0.008		
HDRT x Household size	.046*	0.026		
HDRT x Distance to market	−0.102**	0.047		
WCL x Small ruminant herd size	.027***	0.010	.020**	0.008
WCL x Household size			.042*	0.023
WCL x Distance to market			.123***	0.045
MLK x Literacy in years of education	.041*	0.023		
MLK x Small ruminant herd size			−0.015***	0.006
FEE x Small ruminant herd size	−0.020	0.012		
FEE x Distance to market	.132*	0.075		
Coefficient standard deviation (Unobserved heterogeneity in mean)				
Kid vigor (Strong) [KVS]	.460***	0.089	.335***	0.059
Kid vigor (Medium) [KVM]	.280**	0.110		
Disease tolerance (High) [HDST]	.460***	0.113	.455***	0.071
Disease tolerance (Medium) [MDST]	.332***	0.127		
Heat tolerance (High) [HDRT]	.537***	0.093	.449***	0.064
Heat tolerance (Medium) [MDRT]	.395***	0.095		
Coat color (White) [WCL]	.618***	0.105	.546***	0.065
Coat color (Mixed) [MXC]	.308***	0.119		
Milk (liter) [MLK]	.520***	0.084	.324***	0.056
Price of goat (Birr) [FEE]	.642***	0.156	.991***	0.123
LL		−1110.34		−1258.49
McFadden pseudo R^2		0.431		0.359
AIC		2286.7		2551

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. LL stands for log likelihood at convergence. AIC denotes Akaike Information Criterion. The models were estimated using NLOGIT 6. The estimation commands and additional results are available upon request from the corresponding author.

Table 6
Buck trait non-attendance patterns – comparing all levels and end-point choice experiments.

Class		DCE - All levels Class Probability Model 1.1	Model 1.2	DCE - End point Class Probability Model 2.1	Model 2.2
1	Full attendance	0.128	0.232	0.014	0.072
2	Full non-attendance	0.061	0.126	0.176	0.063
3	Medium body size NA	0.035			
4	Big body size NA	0.001		0.008	
5	Medium kid vigor NA	0.001			
6	Good kid vigor NA	0.009		0.012	
7	Medium disease tolerance – NA	0.347			
8	High disease tolerance – NA	0.011		0.072	
9	Medium drought tolerance – NA	0.147			
10	High drought tolerance – NA	0.002		0.268	
11	Mixed coat – NA	0.085			
12	White coat – NA	0.001		0.376	
13	Market Price – NA	0.173	0.255	0.074	
14	Medium and high disease tolerance - NA		0.246		
15	Medium and high drought tolerance - NA		0.048		
16	Medium drought tolerance and Market price		0.094		
17	Big body size and high drought tolerance – NA				0.183
18	Big body size and white coat – NA				0.062
19	High drought tolerance and white coat – NA				0.457
20	White coat and market price – NA				0.164
BIC		2817.013	2809.403	2416.840	**2343.907**
AIC		2714.652	2728.116	2359.637	**2292.726**
Class. Err.		0.309	0.336	0.218	**0.147**

Note: AIC for Akaike Information Criterion, BIC is Bayesian Information Criterion, and Class. Err. is classification error. The LCM models were estimated using LatentGOLD 5.1.

The same sequence of estimation was followed for the EP data, with the number of classes varying according to the number of traits and the size of the classes. Accordingly, for the EP DCE, the first LCM (Model 2.1) has eight classes. The second model (not reported) has 21 classes, and the third model (Model 2.2 in Table 6) has six classes.

The conventional goodness-of-fit indicators favor the EP design-based ANA models for buck traits. The final models for the two designs have the same number of ANA classes, and yet the EP models have better goodness of fit (Table 6). The ANA patterns between the two designs are very different. When comparing the final estimations made on the AL design data (Model 1.2 and Model 2.2 in Table 6), 23.2% of the respondents considered all the attributes when choosing between the alternative dollars. On the other hand, 25.5% of the respondents ignored market price (Class 13), 24.6% ignored medium drought tolerance and high drought tolerance (Class 14), and 12.6% ignored all attributes. When faced with EP design choice sets, only 1.4% of the respondents considered all traits in choosing between the alternatives, and only 6.3% of the respondents ignored all attributes and made random choices. However, 45.7% of the respondents ignored high tolerance to drought and white coat (Class 19), 18.3% ignored large body size and high tolerance to drought tolerance (Class 17), and 16.4% ignored white coat and market price when choosing bucks (Class 20) (Model 2.2 in Table 6).

The ANA patterns derived from the EP design for bucks are less intuitive compared to those observed based on the AL design. For example, drought tolerance is an important trait and this is what our WTP values indicated. Therefore, the level of nonattendance derived from the EP design is difficult to justify. Similarly, the considerable level of full compensatory behavior implied by the AL design is more meaningful than the negligible level in the EP design, as goats are crucially important in the study areas. We believe that a more elaborate description of the attribute, with a higher number of levels, has allowed describing the heuristics in a more meaningful way (Caputo et al., 2016).

The non-attendance pattern for the DCE trait of doe was analyzed using the same procedure discussed above in relation to bucks. The three LCMs for the AL DCE have 12 (model 1.1), 50 (not reported), and 6 (model 1.2) classes (Table 7). All three models were estimated with full attendance and full non-attendance as the first two classes. The third model (model 1.2 Table 7) included classes with size larger than 5% in the second model (not reported) in addition to the two classes of full attendance and full non-attendance. Similarly, the three LCMs for the EP DCE have 8 models (model 2.1), 16 (not reported), and 8 (2.2) classes

Table 7
Doe trait non-attendance patterns – comparing all levels and end-point choice experiments.

Class		All-levels DCE Class Probability Model 1.1	Model 1.2	End-point DCE Class Probability Model 2.1	Model 2.2
1	Full attendance	0.011	0.043	0.033	0.035
2	Full non-attendance	0.064	0.047	0.237	0.227
3	Medium kid vigor NA	0.001			
4	Good kid vigor NA	0.063	0.139	0.050	
5	Medium disease tolerance – NA	0.138			
6	High disease tolerance – NA	0.001		0.031	
7	Medium drought tolerance – NA	0.654			
8	High drought tolerance – NA	0.003		0.037	
9	Mixed coat – NA	0.048			
10	White coat – NA	0.001		0.575	
11	Milk-NA	0.011		0.029	
12	Market Price – NA	0.008		0.009	
13	Medium kid vigor and doe price		0.125		
14	Medium disease tolerance and Milk -NA		0.101		
15	Milk and Price		0.546		
16	Good kid vigor and white coat – NA				0.255
17	Good kid vigor and milk				0.099
18	High disease tolerance and high drought tolerance				0.059
19	High disease tolerance and white coat				0.192
20	High drought tolerance and white coat				0.056
21	White coat and milk – NA				0.078
BIC		**2390.815**	2427.835	2705.581	2629.325
AIC		**2300.496**	2355.580	2651.390	2575.133
Class. Err.		**0.125**	0.227	0.194	0.218

Note: AIC for Akaike Information Criterion, BIC is Bayesian Information Criterion, and Class. Err. is classification error. The LCM models were estimated using LatentGOLD 5.1.

Table A1
D-error of the four designs.

Card group	Description	D-Error
Choice set group (CSG 1)	CE design for bucks – all levels	0.338
Choice set group (CSG 2)	CE design for does – all levels	0.354
Choice set group (CSG 3)	CE design for bucks – end levels	0.304
Choice set group (CSG 4)	CE design for does – end levels	0.309

(Table 7).

Once again, the models resulted in very different ANA patterns. Focusing on the last constrained models 1.2 and 2.2 (Table 7), full compensatory behavior is very comparable between the two designs. This implies that regardless of the trait levels included, respondents hardly consider all traits in choosing between the doe profiles. Full nonattendance or random choice is still small in the AL design. However, in the EP design, 22.7% of the respondents have ignored all the characteristics and made a random choice.

The trait non-attendance in the AL design is predominantly (54.6%) around combination of milk yield per day and price of doe (Class 15). In the same setting, 13.9% and 12.5% of the respondents ignored good kid vigor (Class 4), and a combination of medium kid vigor and doe price (Class 13), respectively. When faced with EP DCE, 25.5% of the respondents ignored the combination of good kid vigor and white coat (Class 16), while 19.2% ignored high disease tolerance and white coat traits of doe (Class 19). The EP DCEs for doe traits resulted in less convincing ANA patterns in view of the implicit prices we discussed in Section 3.1 above.

Like in the bucks' case above, the ANA patterns derived from the AL DCE are more intuitive. Empirical literature corroborates the high level of nonattendance of market price. Price or the payment mechanism in DCEs is usually the one subjected to nonattendance (Carlsson et al., 2010; Sever, Verbič, & Sever, 2019). The fee is a clear source of disutility for respondents and could be considered as the most hypothetical component of DCEs. On the other hand, the level of random choice and the ignoring of disease tolerance in the case of EP DCE does not align with the implicit prices we presented in Section 3.1 above. Generally, the AL design explains the choice strategies of the respondents better than the EP design.

4. Conclusion

In this study, we elicited and analyzed the preferences of pastoralists for goat attributes prioritized, using all levels (AL) and end point (EP) choice experiments. Willingness to pay for the traits was estimated, preference heterogeneity was investigated, and non-attendance pattern of attributes were analyzed.

Both the AL and EP designs consistently showed that heat/drought tolerance and white coat color are the two most valued traits of the buck followed by disease tolerance. The EP design for does shows that heat/drought tolerance, disease tolerance, and white coat color are the three most important traits followed by child vigor. The heterogeneity in mean RPL models estimated in preference space revealed that the AL design data are more suitable in explaining the unobserved heterogeneity than the EP design data both for bucks and does.

The two designs have also shown differences in explaining attribute non-attendance patterns. In the buck trait DCEs, the AL design has shown a very high level of full compensatory behavior (full attendance) compared to the EP design. In the case of doe DCEs, the EP design has resulted in very high random behavior [ignoring all traits], which is unexpected, given the importance of goats in the area and the knowledge of the respondents about the traits. Therefore, to explain the non-attendance of the attribute, the AL design generated more reliable data.

The consistency of the respondents in their relative preferences for the different traits shows that pastoralists are well aware of the different attributes of their animals and have a clear hierarchy for the attributes in choosing the next generation bucks and does.

Given the challenges they face in water scarcity and diseases, it is not surprising that pastoralists attach the highest weight to heat tolerance/drought and disease resistance traits. Compared to black coated goats, pastoralists preferred white coated ones, because the study areas are very dry and sunny, and the color of the white coat helps to deflect the sunlight and increases the tolerance to heat of the animals. The preference for white is also associated with resistance to trypanosomiasis. Pastoralists know that the tsetse fly, a vector of trypanosomiasis, is attracted to darker coated animals, making them more susceptible to the disease.

Pastoralists were not interested in body size when comparing buck profiles and milk was not of interest when choosing between doe types. The prevalence of drought and disease could be the reasons why pastoralists are not interested in the size of goats. The harsh environment could support only smaller animals, given the challenges of feeding in pastoral areas.

In pastoral and agro-pastoral areas, production traits are of secondary priority, as adaptation is the most important feature the herd livestock keepers would like to have. This explains the relative weights of disease and heat tolerance in both bucks and does. Generally, does are more susceptible to diseases [internal parasites] than bucks, and this may explain the higher WTP for disease tolerance trait in the models for does.

Our study has also compared AL and EP designs to analyze pastoralist preferences. The econometric criteria for model fit often favored end-point design. However, in cases where the results are comparable, the models fit on AL design showed more intuitive and informative parameters. Our findings are in line with the general recommendation that more attribute levels allow better explanation of the choice behavior of the respondents (Caputo et al., 2016; Mariel et al., 2021; Meyerhoff et al., 2015).

Our findings have very clear implications. The definition of breeding goals to improve the goat population in the pastoral and agro-pastoral areas of southern Ethiopia needs to consider our empirical findings. Improved breeds with clear advantage in disease resistance and heat tolerance over local breeds could help pastoralists improve their livelihoods. Information will help develop demand-driven breeding or genetic resource management interventions, which would result in breeds that would address the immediate priorities of the target community and therefore would be adopted. Methodologically, in eliciting preferences for traits or attributes of this nature, the CE design needs to be based on all realistic and relevant levels of the traits to be included.

Our study also has some important limitations. We believe that the sample size per design ($N = 150$) is not large enough. The study could not also include other animals in the area, especially cattle and camel, could reveal interesting patterns in terms of the effectiveness of the design. Therefore, we suggest that studies with larger sample sizes and different animals could ensure more robust empirical estimates.

Finally, all level and end-level designs could generate different results based on the commodity in question and the types of respondents we are working with. This implies that the design phase of DCEs is critically important as it requires clear understanding of the respondents and their perspectives towards related but different goods and services. Therefore, as much as we believe that designs need to be developed strictly based on the research questions and the context, our results encourage using detailed levels of traits/attributes to have better mapping of preferences for quality differentiated goods and services.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests.

Data availability

Data will be made available on request.

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