Vol. 10(8), pp. 262-270, August 2018
DOI: 10.5897/JDAE2018.0920
Article Number: EB2E94D57948
ISSN: 2006-9774

http://www.academicjournals.org/JDAE

ACADEMIC JOURNALS
expand your knowledge

Journal of Development and Agricultural Economics

Full Length Research Paper

Estimating pastoralists' willingness to pay for artificial insemination in arid and semi-arid lands of Kenya

Dickson Nangabo Khainga[1*], Gideon Obare[2] and John Nyangena[1]

[1]Kenya Institute for Public Policy Research and Analysis, P. O. Box 56445-00200, Nairobi, Kenya.
[2]Department of Agricultural Economics and Business Management, Egerton University, P. O. Box 536 -20115, Egerton, Kenya.

Received 10 January, 2018; Accepted 28 June, 2018

Effective promotion of artificial insemination (AI) by private providers in pastoral areas requires stakeholders' opinion in shaping the direction of their adoption. A structured questionnaire was administered to 384 pastoralists in Kajiado and Narok counties, Kenya to elicit data on willingness to pay for AI services. Double bounded contingent valuation methodology was adapted in computing their willingness to pay for AI services. Results revealed that 90% of farmers were aware of AI of which 51.7 and 50.5% were willing to pay for the services in Kajiado and Narok counties respectively, for an average of Kenya Shillings 1, 853, reflecting a premium of 23.6% placed on AI by pastoralists with reference to the base price of Kenya Shillings (KES) 1,500 offered for exotic breeds in Kenyan highlands. Awareness, herd size and access to extension services significantly increase farmers' willingness to pay unlike farm income. The study recommends utilization of existing extension networks of community animal health workers to ensure relevant information about AI is disseminated among pastoralists and perform free AI trials on lead pastoralists' animals to earn others' confidence.

Key words: Artificial insemination, willingness to pay, pastoralists, adoption, contingency valuation, awareness, Maasai.

INTRODUCTION

In Kenya livestock sub-sector is an integral part of the agricultural sector contributing about 4% of the national Gross Domestic Product (GDP) mainly from the production of milk, meat, eggs, hides, skins and wool (KNBS, 2018). The bulk of the livestock are found in arid and semi-arid lands (ASALs), comprising 84% of Kenya's total land mass. These areas are characterized by low, unreliable and poorly distributed rainfall, supports a quarter of the country's total human population of 40.5 million (Ojigo and Dabom, 2013; World Bank, 2010) as well as 60% of the livestock population and most of the country's wildlife (Ngugi and Nyariki, 2005). Most of Kenya's small-scale farmers occupy mainly this region, pursuing traditional livestock production with traditional technologies. These farmers are unlikely to meet the growing demand for food from an increasing population (Leisinger and Schmitt, 1995; GoK, 2012).

Pastoralism is the dominant production system in

*Corresponding author. E-mail: dkhainga@gmail.com. Tel: +254 727 656 984.

Kenya's arid and semi-arid lands (ASALs), but over time, it has been confronted by limited access to better farm technologies, requisite skills and market services (Otieno et al., 2012). Further, weak linkages between research-extension service providers and farmers have hampered adoption of technologies by pastoralists. Until recently, pastoral areas were viewed as net consumers of national wealth, offering poor prospects of return on investment. As a result, productivity and growth have remained relatively low; despite the fact that the sub-sector is expected to play an important role in the development of these areas (Mugunieri and Omiti, 2007; Oluoch-Kosura, 2010).

Over the years the government was the sole provider of animal health services in the country. Empirical evidence however show high-potential areas and market-oriented livestock systems were better served (Oruko and Ndung'u, 2009), while marginal ASALs lacked adequate access to animal health services (Oruko et al., 2000). In mid-1980s, the country implemented the Structural Adjustment Programs (SAPs) which were characterized by market liberalization in the veterinary sector resulting in the gradual reduction of government involvement in the provision of AI services (Richter et al., 1990; De Haan and Bekure, 1991). Liberalization of animal health services started in 1992 with liberation of the pricing policy of milk and milk products followed by privatization and reduced involvement of government in animal breeding and artificial insemination (AI) services; input and veterinary drugs supplies; animal health care and dipping services; de-regulation of the processing and marketing of milk (Mudavadi et al., 2001). To bridge the gap, private sector providers were promoted as an alternative to state provision and as a means to reduce the government financial burden and improve efficiency of AI delivery (Tambi et al., 1999). Privatization of AI services increasingly became a necessity as government funding to veterinary dwindled, with the transfer of activities, functions, responsibilities and property from the public to the private providers.

In the context of AI services, privatization is viewed as a process of refocusing public sector by decentralising responsibilities, not merely as a means of reducing government expenditure, but also as an approach to increase its adoption by farmers in marginal areas, which require knowledge about the current and future demand, disease epidemiology, changing livestock systems, and socioeconomic changes (Kebede et al., 2014). The structural reforms led to reduction of the government and financial burden in the delivery of AI services but witnessed the reduction of farmers demanding the service. Consistent with the reforms, as much as 95% inseminations are now conducted by private AI service providers and cooperatives (Makoni et al., 2014). However, progress has remained slow and livestock production continue experiencing ineffective extension services and low adoption of AI. This is attributed by a myriad of factors among them low demand for AI, vastness of the area, harsh terrain and hostile environment, poor road network infrastructure, which exacerbate the problems posed by the long distances between frontline personnel and pastoralists (GoK, 2010).

The demand response, influenced by the farmers' attitude towards the AI, determines the involvement and efficient delivery of the service in ASALs areas (Tambi et al., 1999). Scholars have argued that the problem of technology adoption by farmers are not only associated with the technology per se but also by socio-economic disparities and environmental challenges (Croppenstedt et al., 2011). From an economic perspective, the benefits of adoption of AI should create sufficient motivation to farmers to adopt the technology since the economic nature of the AI is expected to drive farmers who enjoyed these services to be willing to pay for them (Kartamulia et al., 1995). It has been shown that AI adoption involves decision on investment, transaction and opportunity costs (Ferraro and Simpson, 2002), and its benefits should at least compensate farmers for the associated costs.

Successfully participation of private sector in the AI delivery require preparedness of all actors to engage in open processes and foster the self-confidence and local leadership necessary for their own lessons and capacities to bring about desired outcomes (Kebede et al., 2014). As argued by Rivera et al. (2009), privatization of AI services will depend on farmers' willing to pay for these services and where extension services have previously been provided free of charge, assessment should be made to understand commercial demand for agricultural information.

So far studies have shown that farmers often make decisions regarding uptake of new or improved agricultural technology with enhanced efficiency in delivery, and its adoption depends on awareness about the technology and willingness to pay for it. Establishing the opinion of stakeholders is thus crucial before introduction of a technology since it shapes the direction of their adoption and diffusion (Kimenju and De Groote, 2008). Promoting AI requires determination of the "price" which will not lead to inefficiencies and ineffective outcomes (OECD, 2010; Wunder, 2007). Quantification of these costs is often constrained by lack of information on the factors that a farmer includes in the decision-making process as well as information asymmetries that allows providers to overestimate the opportunity cost of AI delivery. Thus, contingency valuation methods are increasingly being used to estimate the willingness to pay (WTP) on the side of the buyer. Studies evaluating farmer's willingness to pay for AI services among pastoral farmers in Kenya are very rare, thus a knowledge gap. It's on this basis that the study sought to understand pastoralist's willingness to pay for AI and empirically determine farmer's socio-economic characteristics which make them more or less likely towards paying for AI

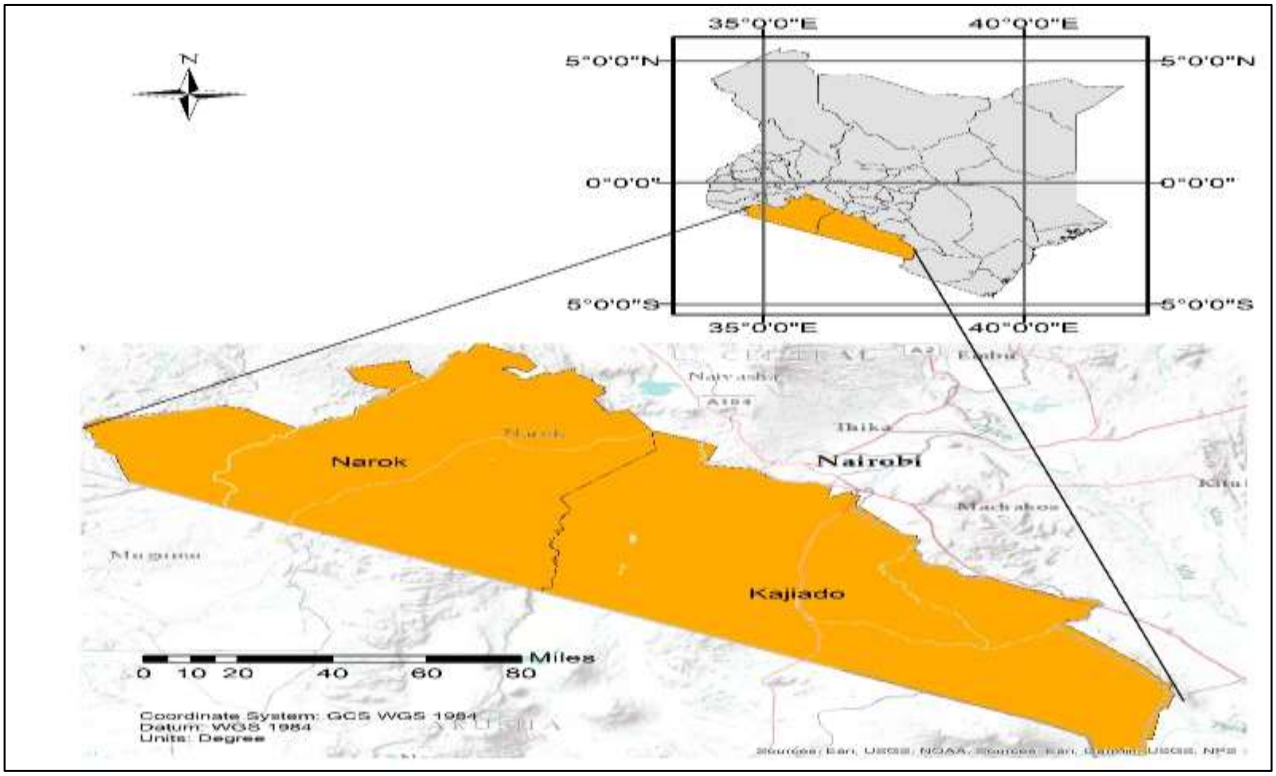

Figure 1. Location of the study area.

services. This information is very important for both County governments and private service providers participating in the provision of AI services in arid and semi-arid lands (ASALs).

MATERIALS AND METHODS

Study area

Data for this study was collected between November 2016 and January 2017 from Narok and Kajiado counties located in southern Kenya (Figure 1). Narok County lies between latitudes 0° 50´ and 1°50´ South and longitude 35°28´ and 36°25´ East covering an area of 17,933 km^2. In 2012, the population of the county was 979,770 and 169,220 households. The county is home to the famous Maasai Mara Game Reserve, one of the most popular tourism destinations in Kenya. The rangelands surrounding the Maasai Mara National Reserve can be divided into three range units based on bio-geographic and climatic differences. The western unit consists mainly of grasslands and comprises the Maasai Mara National Reserve. The Loita Plains stretch out in the North eastern part of the study area and are covered by dwarf shrub and whistling thorn (Acacia drepanolobium) grasslands. The eastern area, with the Siana Hills and Plains, supports Croton dichogamus bush and several other woody species interspersed with grasslands (Stelfox et al., 1986).

The dominant vegetation in the county includes forest land in the Mau area and grasslands and shrubs in the lowland areas of Suswa, in Narok North, Osupuko and Loita divisions in Narok South as well as the Mara sections in Transmara. These areas are suitable for livestock rearing and irrigation. Rainfalls amounts are influenced by the passage of inter tropical convergence zones giving rise to bi-modal rainfall pattern. Long rains are experienced between the months of February and June while the short rains are experienced between August and November. Rainfall ranges from 2,500 mm in wet season to 500 mm during the dry season. In 2017, the population of Narok county was projected to be 1,239,320 (Narok County Government, 2013).

Kajiado county on the other hand is bounded between latitudes 10° 0' and 30° 0' South and longitudes 36° 5' and 37° 5' East with an area of 21,900 km^2. In 2012, the population of the county was 804,796 distributed in 173,464 households (Kajiado County Government, 2013). The main physical features in the County are plains, valleys and occasional volcanic hills ranging from an altitude of 500 m above sea level at Lake Magadi to 2500 m above sea level in Ngong Hills. The county is divided into three different areas namely; Rift Valley, Athi Kapiti plains and Central Broken Ground. Vegetation type in the county is determined by altitude, soil type and rainfall. The county has a bi-modal rainfall pattern, with the short rains fall between October and December while the long rains fall between March and May. The rainfall amount ranges from as low as 300 mm in the Amboseli basin to as high as 1250 mm in the Ngong hills and the slopes of Mt. Kilimanjaro. Temperatures vary both with altitude and season (Amwata, 2013; Bobadoye et al., 2014).

The two counties are inhabited by the Maasai community who are mainly pastoralists, that is, at least 50% of their livelihoods depend on domestic livestock (Swift, 1988). Pastoralists differ from livestock rangers by their practice of taking herds to pasture and water, rather than having fodder grown or brought to them although purely nomadic in the past, many pastoralists are less mobile today (Fratkin and Roth, 2005). Pastoralism is the main source of livelihood to majority of rural households in the both counties. The most common livestock kept are dairy and beef cattle, goat and sheep, with milk, meat, hide and skin, wool and mutton as the main products. Most families move between sedentary and mobile activities, while the larger part of a family, mainly women, children and elderly, have settled down pursuing small scale subsistence farming, some family members (often young men) still take the herds to pastures and water.

Sampling procedure

Multistage sampling technique was used. In the first stage, Keiyan, Kilgoris and Lolgorian divisions of Narok County and Namanga, Mashuru, Ngong and central divisions of Kajiado County were purposively selected because of their large concentrations of Sahiwal cattle populations. Moreover, these are high ranching zones suitable for Sahiwal production. In the second stage, pastoralist populations in these areas were divided into two strata based on their production systems, that is, Agro-pastoralists and Nomadic pastoralists using stratified random sampling technique. Third stage involved acquisition of lists of both nomadic and agro-pastoralists from District Livestock Development Officers (DLPO's) where systematic random sampling technique was applied to each list to obtain 205 agro-pastoralist and 179 nomadic pastoralists households for interview**.**

This sample size was calculated using the proportion sample size determination formula as given by Mugenda and Mugenda (1999).

$$n = \frac{z^2pq}{d^2} = \frac{1.96^2(0.5)(0.5)}{0.05^2} = 384 \quad (1)$$

where *n* is the desired sample size of livestock farmers in Narok and Kajiado Counties, *z* is the standard normal deviate at the required confidence level, *p* is the proportion in the target population estimated to have characteristics of interest, *q* is 1- *p,* and *d* is the level of statistical significance set.

Analytical framework

Following the analytical framework of Hanemann et al. (1991), WTP for AI services by respondents was estimated using open-ended questions asking the respondents to declare the maximum amount they would be willing to pay, or close-ended, asking the respondents if they would be willing to pay a specific amount or not (dichotomous choice). In the current study, a closed-ended question approach was adopted given that most of the pastoralists were aware of the AI but could not arbitrarily attach a true value to the service. Moreover this approach is easier and more realistic since questions correspond more to a real market situation. On the other hand, the open-ended format is appropriate when the farmer is well informed about the new technology or product and its characteristics. However, literature indicates that such an approach would be misleading if the respondent lacks appropriate information and incentives to comprehensively determine the values to attach if a market were to exist (Boyle, 2017).

The use of contingent valuation (CV) methods to estimate farmers' valuation of non-market goods or new technologies as developed by social economists is not common, but it is widely used in environmental studies, wildlife conservation and natural resource economics (Hanemann et al., 1991). The technique is appropriate in imploring producers' WTP for a product that is not yet on the market, such as AI. Applicability of this approach demands that the researcher crafts a hypothetical market for non-market good, requests a set of subjects to operate in that market, and records the outcomes. The values generated through this hypothetical market are treated as estimates of the value of the non-market good or service (Mitchell and Carson, 1989).

In many transactions, farmers are offered a technology at a given price such that after considering his ability to buy, the decision is then reached on whether to buy or not. Estimating WTP using single-bounded method, the individual only responds to one bid which is incentive-compatible; it is in the respondent's strategic interest to say "yes" if his WTP is greater or equal to the price asked, and "no" otherwise (Mitchell and Carson, 1989). Utility maximization implies that a farmer will then only answer "yes" to the offered bid if his maximum WTP is greater than the bid. However, the single-bounded method requires a large sample size and is statistically inefficient (Hanemann et al., 1991). In order to ensure efficiency of the estimates, double bounded method was adapted by offering the respondent a second bid, higher or lower depending on the first response. This approach includes more information about the respondents WTP and, therefore, provides more efficient estimates and tighter confidence intervals (ibid). Table 1 presents the definition of variables included in the model used.

The respondent was asked if he/she was willing to pay an amount B_i, for the provision of AI services on his farm per animal. If the farmer answers no then it can be assumed that $0 \le WTP < B_i$, if he answers yes then $B_i \le WTP < \infty$. More explicitly, the respondents will fall within one of the following categories: The farmer answers yes to the first question and no to the second question, then $B_i^u > B_i$ thus it can be inferred that $B_i \le WTP < B_i^u$. The individual answers yes to the first question and yes to the second question, then $B_i^u \le WTP < \infty$. The individual answers no to the first question and yes to the second question, then $B_i^d < B_i$ thus conclude that $B_i^d \le WTP < B_i$. The individual answers no the first and second questions, then we have $0 < WTP < B_i^d$.

Adapting the modelling framework of Hanemann et al. (1991), the likelihoods of these outcomes are π^{yy}, π^{nn}, π^{yn}, π^{ny}, respectively. Under the assumption of utility-maximizing farmer, the formulas for these likelihoods are as shown below. In the first case where the respondent accepts the initial and second higher bid, we have $B_i^u > B_i$;

$$\pi^{yy}(B_{i,} B_i^u = \Pr\{B \le \max WTP and\ B_i^u \le \max WTP\}$$
$$= \Pr\{B_i \le \max WTP \mid B_i^u \le \max WTP\} \Pr\{B_i^u \le \max WTP\}$$
$$= \Pr\{B_i^u \le \max WTP\} \quad (2)$$

In the second case where the respondent rejects the initial bid and second lower bid, we have $B_i^d < B_i$;

$$\pi^{nn}(B_i, B_i^d) = \Pr\{B_i > \max WTP\ and\ B_i^d > \max WTP\} \quad (3)$$

Third case is where the respondent accepts the initial bid and rejects the second bid, we have $B_i^u > B_i$;

$$\pi^{yn}(B_i, B_i^u) = \Pr\{B_i \le \max WTP \le B_i^{u\}} \quad (4)$$

The last case is where the respondents rejects the initial bid and accepts the second bid, we have $B_i^d < B_i$;

$$\pi^{ny}(B_i, B_i^d) = \Pr\{B_i \ge \max WTP \ge B_i^d\} \quad (5)$$

Computing the mean willingness to pay, a logistic curve was specified, fitted on the data and estimated. The log-likelihood function was then defined as follows and estimated:

$$\ln^{D}(\theta)=\sum_{i=1}^{N}\{d_i^{yy}\ln\pi^{yy}(B_i,B_i^u)+d_i^{nn}\ln\pi^{nn}(B_i,B_i^d)+ d_i^{yn}\ln\pi^{yn}(B_i,B_i^u)+d_i^{ny}\ln\pi^{ny}(B_i,B_i^d) \quad (6)$$

where $d_i^{yy}, d_i^{nn}, d_i^{yn}$ and d_i^{ny} are binary-valued indicator variables.

The final step was to specify and estimate a WTP regression model to determine factors influencing WTP. The regression method allows inclusion of other factors in the analysis, in particular socioeconomic characteristics of the respondents to explain the bidding behaviour. However, WTP can be computed with or without inclusion of covariates in the modelling strategy as illustrated by Lopez-Feldman (2012).

RESULTS AND DISCUSSION

Farmers' awareness and willingness to accept AI services

Prior to establishing the extent to which farmers would be willing to pay for AI, it is imperative that we determine if they are aware of this technology. To illustrate this, descriptive analysis was carried out and the results presented in Figure 1. It was evident that 89.9 and 90.3% of farmers in Kajiado and Narok Counties respectively knew about the existence of AI services. This provides much needed background upon which sensitization needs to be built in order to achieve maximum diffusion of the technology. However, awareness of AI does not guarantee its uptake as noted by Chinese consumers towards biotech rice. Lin et al. (2006) found that consumers who were aware of biotech foods were less inclined to purchase biotech rice than those who had no or little awareness. Moreover, the impact of the awareness variable was not statistically significant in the case of biotech soybean oil (ibid).

Despite high levels of awareness, most farmers still use the natural service method as the major breeding method. This could be attributed to the fact that accessibility of the services is still a major challenge due to infrastructural constraints, faith in the technique and the communities' preference for bull service as reported by Janssen-Tapken et al. (2006). Inadequacy in number of AI technicians and accompanying inputs would hamper farmers' access to and adoption AI technology (Kassa and Wuletaw, 2018). Despite AI as a technology being technically beneficial, lack of appropriate delivery system, its adoption and effectiveness in pastoral areas is declining. The consequence of this fall is undesirable because the genetic potential and productivity of the dairy herd in ASALs is bound to decline very rapidly.The inadequate incentives for both public and private breeders to practice in ASALs have been a major hindrance to the spread of AI services across from the highlands to the ASALs.

The long distances that must be covered by a service provider between one household to another in ASALs and to the nearest markets and the cost incurred outweigh the revenues that are likely to be generated from such business. This therefore necessitates deliberate government intervention in deploying public AI service providers and facilitates their movements within these areas (ibid).

The decision to pay for a particular technology depends solely on the prior response on the willingness to accept it. This underscores the importance of qualitative studies on perceptions of both producers and consumers of services and goods before introducing them in the market. The question of amount is only relevant if the farmer is willing to accept AI otherwise a hypothetical scenario has to be created to entice him to reveal his willingness to accept (Boyle, 2017). This is based on the assumption that there are underlying constraints to access AI (accessibility, cost and success rate) such that if they are addressed then they may be willing to value the technology. Figure 2 indicates that among farmers who were aware of AI (89.9% in Kajiado and 90.3% in Narok), 38.8% from Kajiado were willing to accept and adopt compared to their counterparts (23.3%) in Narok County. This implies that farmers have reservations about the adoption of AI despite wide spread knowledge about AI. Current study findings are inconsistent with the findings of Dehinenet et al. (2014) who found awareness of diary technologies through livestock training to have increased farmer's probability of adopting and owning the improved technologies.

Monetary valuation for artificial insemination in pastoral areas

To ensure sustainability of the technology in pastoral areas, farmers were presented with different bids to establish amount they were willing to pay for AI. On average, 51.7% of the sampled farmers in Kajiado were willing to pay the initial bid proposed to them. Table 2 illustrates farmers bidding behavior with respect to different bids that were given.

The results also indicates that as the bid increases from KES 600 to KES 3000, the number of farmers affirming their ability to incur that cost declines. This is rational of farmers because as the cost of a new technology increases, given their cost outlay, they pursue a minimization objective and keep their production goals intact. The second bid is contingent on the response and amount indicated by the farmer in the initial bidding (Hanemann et al., 1991; Boyle, 2017). It is evident from Table 3 that farmers were willing to pay a second bid 48.9 and 50.5% in Kajiado and Narok counties respectively. The second bid offered was either a discount to the first bid offered for those farmers who declined to pay initial bid or a premium on the initial bid

Table 1. Variable definition for contingent valuation.

Name of the variable	Definition
B_i	Initial bid in KES
B_i^u	Second higher bid in KES if answer to initial bid was yes
B_i^d	Second lower bid in KES if answer to initial bid was no
Nn	= 1 if the answer to the WTP questions was no, no
Ny	= 1 if the answer to the WTP questions was no, yes
Yn	= 1 if the answer to the WTP questions was yes, no
Yy	= 1 if the answer to the WTP questions was yes, yes
Awareness	=1 if the farmer has ever heard of AI in the last 5 years
Credit	=1 if the farmer had access to credit facilities in the last 12 months
Herd size	Current total number of cattle owned by farmer
Extension	=1 if farmer had access to extension services
Education	Number of years of schooling
Age	Number of years the farmer has been living
Household size	Number of household membership
Off-farm income	=1 if farmer earns some extra income from off-farm activities

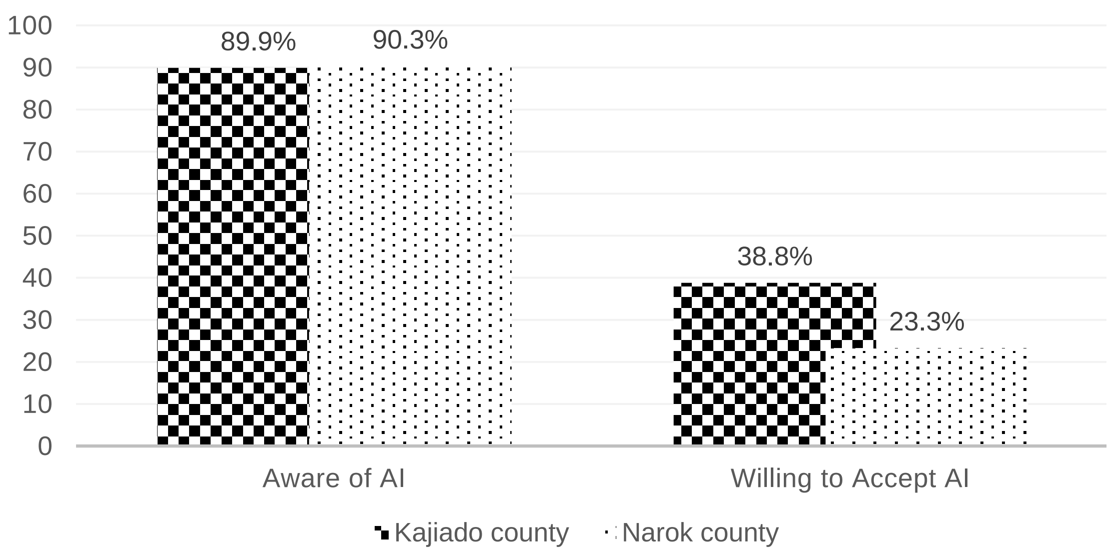

Figure 2. Distribution of farmers' awareness and willingness to accept artificial insemination services in the last 5 years.

Table 2. Bidding pattern for the initial bid.

County	WTP the first bid	The amount the farmer is willing to pay for artificial insemination						
		KES 600	KES 1200	KES 1800	KES 2400	KES 3000	Total	
Kajiado County	No	4	2	34	18	28	86	48.3%
	Yes	36	13	19	16	8	92	51.7%
	Sub-sample	40	15	53	34	36	178	100%
Narok County	No	5	7	42	16	32	102	49.5%
	Yes	33	12	40	6	13	104	50.5%
	Sub-sample	38	19	82	22	45	206	100%
Sample		78	34	135	56	81	384	

Table 3. Bidding pattern for the second bid.

County	WTP the first bid	The amount the farmer is willing to pay for artificial insemination							
		KES 400	KES 800	KES 1500	KES 2000	KES 2800	KES 3600	Total	
Kajiado County	No	0	9	23	24	30	5	91	51.1%
	Yes	4	29	24	13	14	3	87	48.9%
	Sub-sample	4	38	47	37	44	8	178	100%
Narok County	No	1	6	21	38	27	11	104	49.5%
	Yes	4	34	33	18	11	2	102	50.5%
	Sub-sample	5	40	54	56	38	13	206	100%
Sample		9	78	101	93	82	21	384	

Table 4. Double bounded contingent valuation without covariates.

Variable	Coefficient	Standard err	Z	P value
Beta constant	1881.25	50.79	37.04	0.00
Sigma constant	844.13	43.28	19.50	0.00
Number of observations		384		

for the farmer who were willing to pay initial bid as the true price for getting AI. The bidding behaviour of farmers towards the second bid was similar such that as the amount increases, then few are willing to incur such cost as can be seen when bid rises from KES 400 to KES 3600 as shown in Table 3.

Table 4 shows results of a double bounded contingent valuation approach without including covariates. The results revealed an average of KES 1881.25 as the mean WTP for AI by pastoralists in ASALs of Kajiado and Narok Counties. This reflects a premium of 25.4% placed on AI by pastoralists with reference to the base price of KES 1500 offered for exotic breeds in Kenyan highland.

However, the bidding decision by the farmer is informed by various factors including his awareness towards AI, access to credit facilities to finance new technologies, herd size, household size, age, education levels, access to extension services, and his off-farm income. It's worth noting that in expressing the amount they are willing to pay for the provision of the service, there is implied price comparison between the cost of the bid and the cost of acquiring the bull. Sahiwal bull at market price at that time was KES 120,000 if bought from KALRO – Naivasha and KES 80,000 if bought from the local markets. However, the survey revealed that most Sahiwal farmers interested in replacing the bull or acquiring an extra one would prefer getting it from KALRO. Inclusion of factors influencing the bidding behavior of the farmer, the Mean WTP for AI services reduces to KES 1853.19. This reflects a deviation of KES of 353.19 (23.5% of base price of KES 1500). As indicated in Table 5, awareness, herd size and access to extension had significant positive influence while farm income had significant negative effect on farmer's bidding process.

Knowledge about the existence of a good or technology by the farmer influences his decision to approve its uptake. In the current study, farmers awareness was found to positively influence his WTP for AI. Exposure to information on AI technology increases the probability of accepting a higher bid by 68.3%. These results corroborate findings of Ghosh et al. (2005) that have knowledge about AI, green fodder feeding, concentrate feeding and communication source directly and indirectly promotes the adoption of AI among dairy farmers of both co-operative and non-member co-operative societies. However, current study results are contradicted by study findings of Lin et al. (2006) who found consumers with exposure or awareness of biotech rice to be less inclined to purchase biotech rice than those who have no or little awareness. This implies that targeting the dissemination of information to farmers with the least exposure or no awareness would be a more effective strategy to achieve sustainability of AI technology in pastoral areas

Farmers herd size had a positive significant effect on farmer's WTP for AI. This could be attributed to the fact that farmers with large herd sizes found it economical to use AI than to procure the bull which is more expensive compared to the cost of AI. Moreover, repeated use of same bull leads to in-breeding. Inbreeding in pastoral areas is a reality given the fact that most farmers do not keep record as established from our survey and this explains low livestock productivity levels experienced by most pastoralists.

Effective extension services in ASALs could aid pastoralists in using AI in improving their herd's fertility

Table 5. Parameter estimates for WTP model for AI with covariates.

Variable	Coefficient	Standard err
Awareness	0. 683***	0.242
Credit	0.192	0.164
Herd size	0.001*	0.001
Extension	0.643***	0.147
Education	0.022	0.050
Age	-0.135	0.098
Household size	-0.01	0.013
Off-farm income	0.533***	193
Number of observations	384	
LR Chi2(8)	119	
Prob > Chi2	0.00	
Mean WTP	1853	

***, ** and * refers to statistically significant at 1, 5 and 10% respectively and the p values are in parenthesis.

through exchange of desired genetic materials thereby replacing less productive cattle breeds. However, lack of quality breeding services and perceived costs and risks has been their greatest hindrance in its adoption (Ericksen and Crane, 2018). Access to extension had positively significant effect in establishing farmer's WTP for AI. Availability of relevant information from credible sources has the effect of influencing farmer's preferences towards a new technology. Innovative approaches by promoters of a technology through extension officers and existing infrastructure have the probability to yield its sustainability upon their exit in agricultural subsector (Omondi et al., 2017).

Farmer's ability to purchase new technologies depends on his/her disposable income given existing production cost outlay. In this study, off-farm income had a positive significant effect in establishing farmer's WTP for AI services in pastoral areas. This could be attributed to the fact that pastoralists with extra income have the ability to buy more productive technologies to increase their output. These results confirm findings of Kimenju and De Groote (2008) who found consumers with higher income to have high WTP for fortified maize. Availability of off-farm income has a positive effect on technology adoption with little necessity to seek credit from lending facilities for most farmers in rural areas (Mwangi and Kariuki, 2015; Mmbando and Lloyd, 2017). This implies that farmers with off-farm income have higher propensity for new technologies.

CONCLUSIONS AND RECOMMENDATIONS

To ensure sustainability of the adopted technology, it is imperative that the beneficiaries be willing to financially and materially support its existence. In the current study, most farmers showed their willingness to accept AI technology despite challenges in accessing service providers. Existence of enabling market environment will motivate private service providers to operate in Kenyan pastoral areas. It was established that most farmers were WTP an average of KES 1853.2 for AI per cow. This reflects a premium of 23.6% placed on AI by pastoralists with reference to the base price of KES 1500 offered for exotic breeds in Kenyan highland. It is therefore recommended that both county governments and non-governmental organizations organize field days for pastoralists so that relevant information about AI is disseminated and free trials done on lead farmers. Moreover, government should consider ensuring high quality semen is distributed to pastoralist at subsidized rate till they gain confidence in the technology. This is because adoption of AI has the potential in easing the demand of the Sahiwal bull from an already limited supply.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

REFERENCES

Amwata DA (2013). The influence of climate variability and change on Land–use and Livelihoods in Kenya's Southern rangelands. A PhD thesis submitted to the Department of Land Resource Management and Agricultural Technology, University of Nairobi.

Bobadoye AO, Ogara WO, Ouma GO, Onono JO (2014). Comparative analysis of rainfall trends in different Sub-Counties in Kajiado County Kenya. International Journal of Innovative Research and Studies 3:12.

Boyle KJ (2017). Contingent Valuation in Practice. In: Champ P., Boyle K., and Brown T. A Primer on Nonmarket Valuation. Springer, Dordrecht. The Economics of Non-Market Goods and Resources P 13.

Croppenstedt A, Demeke M, Meschi MW (2011). Technology adoption in the presence of constraints: the case of fertilizer demand in Ethiopia. Review of Development Economic 7:1467-9361.

de Haan C, Bekure S (1991). Animal health services in sub-Saharan Africa: Initial experiences with alternative approaches. The World Bank.

Dehinenet G, Mekonnen H, Kidoido M, Ashenafi M, Guerne Bleich E (2014). Factors influencing adoption of dairy technology on small holder dairy farmers in selected zones of Amhara and Oromia National Regional States, Ethiopia. Discourse Journal of Agriculture and Food Sciences 2(5):126-135.

Ericksen P, Crane T (2018). The feasibility of low emissions development interventions for the East African livestock sector: Lessons from Kenya and Ethiopia. Nairobi, Kenya: International Livestock Research Institute (ILRI). ILRI Research Report 46.

Ferraro P, Simpson R (2002). The cost effectiveness of conservation payments. Land Econ. 78(3):339-353.

Ghosh, RK, Goswami, A and Mazumdar AK. (2005). Adoption behaviour of the dairy farmers in relation to artificial insemination in co-operative farming system. Livestock Research for Rural Development 17(3):35-42.

Government of Kenya (GoK) (2012). Vision 2030 Development Strategy for Northern Kenya and other Arid Lands. Ministry of State for Development of Northern Kenya and other Arid Lands, Nairobi.

Government of Kenya (GoK) (2010). Agricultural sector development strategy 2010–2020. Ministry of Agriculture, Nairobi.

Hanemann M, Loomis J, Kanninen B (1991). Statistical efficiency of double-bounded dichotomous choice contingent valuation. American Journal of Agricultural Economics 73(4):1255-1263.

Janssen-Tapken U, Kadarmideen HN, Rohr PV (2006). Cattle breeding strategies using genetic markers as a pathway for improving competitiveness of pastoral systems in Kenya. Paper read at a Policy Research Conference on Pastoralism and Poverty Reduction in East Africa, 27-28, June, Nairobi, Kenya. http://www.saga.cornell.edu/saga/ilri0606/32janssen-tapken.pdf.

Kajiado County Government (2013). County Integrated Development Plan (CIDP) 2013-2017, Kajiado County Government.

Kartamulia I, Miniswaty A, Knipscheer H (1995). Development of a private animal health delivery network in North Sumatra, Indonesia. Agriculture and Human Values, Winter 12(1):39-44.

Kassa F, Wuletaw W (2018). Assessment of the problems associated with artificial insemination practices in Essera Woreda, Dawuro zone, Southern Ethiopia. International Journal of Livestock Production 9(2):24-28.

Kebede H, Melaku A, Kebede E (2014). 'Constraints in animal health service delivery and sustainable improvement alternatives in North Gondar. Ethiopia' Onderstepoort Journal of Veterinary Research 81(1):713.

Kimenju SC, De Groote H (2008). Consumers' willingness to pay for genetically modified food in Kenya. Agricultural Economics 38(1):35-46.

Kenya National Bureau of Statistics (KNBS) (2018). Economic Survey, Government printer, Nairobi.

Lin W, Somwaru A, Tuan F, Huang J, Bai J (2006). Consumers' willingness to pay for biotech foods in china: A contingent valuation approach. AgBioForum 9(3):166-179.

Lopez-Feldman A (2012). Introduction to contingent valuation using Stata. https://mpra.ub.uni-muenchen.de/id/eprint/41018

Makoni N, Hamudikuwanda H, Chatikobo P (2014). Market study of AI and vaccine production value chains in Kenya. Report commissioned by the embassy of the Kingdom of Netherlands in Nairobi, Kenya.

Mitchell RC, Carson RT (1989). Using surveys to value public goods: The contingent valuation method. Resources for the Future, Washington DC.

Mmbando FE, Lloyd JSB (2017). Socio-economic and Institutional Factors Influencing Adoption of Improved Maize Varieties in Hai District, Tanzania, Journal of Human Ecology 53(1):49-56,

Mudavadi PO, Otieno K, Wanambacha JW, Odenya JO, Odendo M, Njaro OK (2001). Smallholder dairy production and marketing in western Kenya: A review of literature. Smallholder Dairy (Research and Development) Project Research Report, ILRI, Nairobi, Kenya. http://hdl.handle.net/10568/1781.

Mugunieri GL, Omiti JM (2007). Decentralization, community-based organizations and access to agricultural extension services in eastern Kenya. In: Barrett, C.B., Mude, A.G., Omiti, J.M. Decentralization and the Social Economics of Development: Lessons from Kenya. CAB International, Wallingford pp. 64-83.

Mwangi M, Kariuki S (2015). Factors Determining Adoption of New Agricultural Technology by Smallholder Farmers in Developing Countries. Journal of Economics and Sustainable Development 6(5):208-216.

Narok County Government (2013). County Integrated Development Plan (CIDP) 2013-2017, Narok County Government.

Organization for Economic Co-operation and Development (OECD). (2010). Paying for Biodiversity: Enhancing the Cost-effectiveness of Payment for Ecosystem Services. Organization of Economic Co-operation and Development (OECD), Paris.

Ojigo OD, Dabom JC (2013). Communications and Data Collection: Lessons from Studies in the Extensive Livestock Production Areas of Kenya Journal of Exotic Pet Medicine. 22(1):39-45.

Oluoch-Kosura W (2010). Institutional innovations for smallholder farmers' competitiveness in Africa. African Journal of Agricultural and Resource Economics 5(1):227-242.

Omondi I, Zander K, Bauer S, Baltenweck I (2017). Understanding farmers' preferences for artificial insemination services provided through dairy hubs. Animal 11(4):677-686.

Oruko L, Ndung'u L (2009). An analysis of animal healthcare service delivery in Kenya. Institutional Economics Perspectives on African Agricultural Development. International Food Policy Research Institute pp. 257-272.

Oruko O, Leonard DK, Upton M, McLeod A (2000). Restructuring of animal health services in Kenya: constraints, prospects and options. Development Policy Review 18:123-138.

Otieno DJ, Hubbard L, Ruto E (2012). Determinants of technical efficiency in beef cattle production in Kenya. International Association of Agricultural Economists (IAAE) Triennial Conference, Foz do Iguacu, Brazil, 18-24 August, 2012.

Richter W, Freeland G, Huhn JE (1990). Privatization of Livestock Services. Proceedings of a Workshop at Feldafing/FRG, GTZ, Feldafing, Germany.

Stelfox JG, Peden DG, Epp H, Hudson RJ, Mbugua SW, Agatsiva JL, Amyunzu CL (1986). Herbivore dynamics in south Narok, Kenya. Journal of Wildlife Management 50(2):339- 347.

Tambi EN, Mukhebia AW, Mainaa OW, Solomon MH (1999). Probit analysis of livestock producers' demand for private veterinary services in the high potential agricultural areas of Kenya. Agricultural Systems 59:163-176.

Wunder S (2007). The efficiency of payments for environmental services in tropical conservation. Conservation Biology 21(1):48-58.