FACTORS INFLUENCING ADOPTION OF ARTIFICIAL INSEMINATION BY SMALLHOLDER LIVESTOCK FARMERS IN DRYLAND PRODUCTION SYSTEMS OF KENYA

BY

MAJOK DAN ABOT

A56/11808/2018

A THESIS SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF MASTER OF SCIENCE IN AGRICULTURAL AND APPLIED ECONOMICS

DEPARTMENT OF AGRICULTURAL ECONOMICS

FACULTY OF AGRICULTURE

UNIVERSITY OF NAIROBI

2020

DECLARATION

This thesis is my original work and has not been submitted in any university for the award of any degree.

Majok Dan Abot

Reg, No. A56/11808/2018

Signature: Date: 28th November 2020

This thesis has been submitted with our approval as university supervisors:

1. Dr. David Jakinda Otieno

Signature ____________________ Date: 28th November 2020

Department of Agricultural Economics, University of Nairobi

2. Prof. Willis Oluoch-Kosura

Signature Date: November 28th, 2020

Department of Agricultural Economics, University of Nairobi

DECLARATION OF ORIGINALITY

UNIVERSITY OF NAIROBI

Declaration of Originality Form

This form must be completed and signed for all works submitted to the University for examination.

Name of Student MAJOK DAN ABOT

Registration Number A56/11808/2018

College CAVs

Faculty/School/Institute AGRICULTURE

Department AGRICULTURAL ECONOMICS

Course Name M.SC IN AGRICULTURAL AND APPLIED ECONOMICS

Title of the work

FACTORS INFLUENCING ADOPTION OF ARTIFICIAL INSEMINATION BY THE SMALLHOLDER LIVESTOCK FARMERS IN DRYLANDS PRODUCTION SYSTEMS OF KENYA

DECLARATION

1. I understand what Plagiarism is and I am aware of the University's policy in this regard
2. I declare that this THESIS (Thesis, project, essay, assignment, paper, report, etc) is my original work and has not been submitted elsewhere for examination, award of a degree or publication. Where other people's work, or my own work has been used, this has properly been acknowledged and referenced in accordance with the University of Nairobi's requirements.
3. I have not sought or used the services of any professional agencies to produce this work
4. I have not allowed, and shall not allow anyone to copy my work with the intention of passing it off as his/her own work
5. I understand that any false claim in respect of this work shall result in disciplinary action, in accordance with University Plagiarism Policy.

Signature [signature]

Date 28/11/2020

DEDICATION

Special dedication to my lovely mother Elizabeth for her sincere love and prayers toward my studies. May the Almighty God give her good health to taste the fruits of my pursuit of education.

ACKNOWLEDGEMENT

This thesis is based on research work supported by the United States Agency for International Development (USAID), as part of the Feed the Future Initiative, under the Consultative Group for International Agricultural Research (CGIAR) Fund, award number BFS-G-11-00002, and the predecessor fund the Food Security and Crisis Mitigation II grant, award number EEM-G-00-04-00013.I acknowledged them for the financial support provided.

Special appreciation also goes to my supervisors Dr. David Jakinda Otieno and Prof. Willis Oluoch-Kosura for their great insights that contributed to my thesis writing. Their valuable guidance, support and dedication have made it possible for me to complete my masters' study.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS

ADC	Agricultural Development Corporation
AI	Artificial Insemination
ASALs	Arid and Semi-Arid Lands
CIDP	County Integrated Development Programme
DFID	Department for International Development
EU	European Union
FAO	Food and Agriculture Organization of the United Nations
GDP	Gross Domestic Product
IPCC	Intergovernmental Panel for Climate Change
KAGRC	Kenya Animal Genetic Resource Centre
KCC	Kenya Co-operative Creameries
KIPPRA	Kenya Institute for Public Policy Research and Analysis
KMC	Kenya Meat Commission
KNBS	Kenya National Bureau of Statistics
LPM	Linear Probability Model
MLE	Maximum Likelihood Estimation
OLS	Ordinary Least Square
RUM	Random Utility Model
SDG	Sustainable Development Goal
SEAZ	Small East African Zebu
SGR	Standard Gauge Railway
UN	United Nations
UNPD	United Nations Population Division

USA	United States of America
USAID	United States Agency for International Development
USDA	United States Department of Agriculture
VAT	Value Added Tax
VIF	Variance Inflation Factor

ABSTRACT

Increasing human population in recent decades has mounted pressure on food supply including livestock products. Livestock is the main source of livelihood to the poor households in the drylands of sub-Saharan Africa (SSA) such as parts of Kenya. Therefore, increasing its productivity is necessary to improve the welfare of poor rural households in the arid and semi-arid lands (ASALs). One of the viable ways to improve livestock productivity is by embracing the utilization of artificial insemination (AI) services. However, empirical evidence on level of AI uptake in ASALs remains scanty. In order to address this knowledge gap, the current study assessed factors influencing the uptake and intensity of AI adoption by the smallholder livestock farmers in dryland production systems of Kenya.

The study used primary survey data that was collected through structured questionnaires administered to 398 randomly selected smallholder livestock farmers. The double-hurdle model (comprising probit and truncated regressions) was applied to analyse factors influencing the adoption and intensity of use of AI technology by smallholder livestock farmers. The results showed that, the overall adoption rate was 13.3%, while it was 21% and 1.8% in Makueni and Kajiado Counties, respectively. The probit regression results indicated that, access to extension services, age of household head, education level of household head, contract farming and cattle farm size had positive influence while, household size, off-farm employment, access to information, group membership and distance from home to nearby open-air livestock markets had negative influence on AI adoption. The truncated regression results revealed that, distance from home to nearby AI centre, household size, and access to information positively influenced the extent of AI adoption. On the contrary, dishonesty of the service providers, education level of household head and distance to nearby livestock markets had negative effects on extent of AI adoption.

Based on the low adoption rate found in the study area and the significant variables, the study recommends application of information communication technology (ICT) such as the use of mobile messaging system to promote extension services, training and dissemination workshops to smallholder farmers, promotion of pastoral education in Kajiado and expansion of AI centres as policy options to encourage the adoption of AI technology in the drylands of Kenya.

Key words: livestock farmers, drylands, artificial insemination.

CHAPTER ONE: INTRODUCTION

1.1 Background Information

The world population is increasing at alarming rate and is expected to surpass the resources available for sustaining human lives. It is estimated that the world population will be 9.15 billion in 2050 (UNPD, 2008). With the expected population increase, there will probably be emergence of middle-class consumers estimated to be 3 billion who will need more food. The majority of this population will come from developing countries especially Africa where poor and vulnerable people are abundant.

A large part of African land mass is predominantly arid and semi-arid land (ASAL) making rain-fed farming almost impossible and as a result, the population living there are in acute destitution and can barely afford one meal per day. Therefore, to end poverty and achieve zero hunger as advocated by the United Nations (UN) through the United Nations Sustainable Development Goals (SDGs), there is a need to prioritize livestock production in both high potential areas and ASALs.

Agriculture, which is considered to be the mainstay of Kenya's economy contributes 31.5% to the country's gross domestic product (GDP) (KIPPRA, 2018). The livestock sub-sector contributes 4% of Kenya's GDP (KNBS, 2018a). According to the 2019 Kenya population and housing census, there are 15.8 million cattle in Kenya; 10,961320 beef and 4,838480 dairy cattle (MoALF, 2020). Most of the beef cattle are of indigenous origin, while the dairy cattle are exotic and crosses (indigenous and exotic mix). The indigenous cattle are kept in the ASALs because of their ability to withstand high temperatures. The common indigenous cattle breeds found in ASALs are the Zebu, Boran, Sahiwal, and their crosses. It is estimated that, slightly more than three-quarters of cattle herds in Kenya are kept by pastoralists who supply the bulk of meat consumed in the country (Wakhungu et al., 2014).

Pastoralism is a source of livelihoods with approximately 20 million people and supply almost all the entire meat consumed in East Africa (Nyariki, 2017).

The livestock sub-sector is under immense pressure to adapt to meet the rising demand for increasing livestock products and enhance the socioeconomic stability of smallholder livestock farmers in the ASALs. In order to address this challenge, it is inevitable to increase livestock productivity. However, the most dominant production systems in the ASALs are nomadic pastoralism and agro-pastoralism, which are based on traditional production methods with minimal or no use of purchased high yielding inputs and technologies.

Nomadic pastoralists normally have communal open grazing land. They move sporadically in search for pastures and water for their livestock. Natural grass is the main feed resource/pasture for animals in this system of production. This system is believed to be environmentally sustainable and it is commonly practiced in ASALs especially in northern and southern (Maasai) parts of Kenya. They are currently facing a number of challenges, in particular rapid urbanization. Their grazing fields have been encroached by increased settlements and can no longer freely graze their cattle as before (Little and McPeak, 2014). It is projected that the impact of climate change in form of global warming will be more appalling in Africa than in other parts of the world (IPCC, 2014). In that regard, the population living in the ASALs who are practicing pastoralism as source of their livelihoods will be victims of climate change (Thornton et al., 2008).

The agro-pastoralism system on the other hand, involves keeping livestock and at the same time growing crops. The system is practiced for subsistence in semi-arid regions. The advantage of this system is that, both crops and livestock benefited from each other as crop residues are used for feeding livestock and cow dung is used as organic manure to increase soil fertility for crops production. The land degradation is one of the major factors facing agro-pastoral communities living in the ASAL. Overall, high rates of land cover change are experienced within regions where land productivity is highly dependent on socio-economic drivers. In the end, climatic and environmental conditions limit intensive agricultural and pastoral activities (Vacquire et al., 2015).

The nomadic pastoralism and agro-pastoral systems are very important in production of dairy and beef in the ASALs of Kenya. All dairy species in Kenya produced an estimated 3 billion litres milk annually (KIPPRA, 2018). Cattle produce about 88% while the rest comes from camels and goats.

Expanding dairy production is worthwhile since it is a critical source of livelihood for over 600,000 smallholder farmers in Kenya (Mutembei et al., 2015). The smallholder farmers are the cornerstone of the dairy industry contributing approximately more than 70% of the entire milk sold. Increasing efficiency within the dairy industry is vital for improving nutrition status, farm incomes, alleviating poverty and meeting the gap in demand for dairy products for the ever-growing population. In order to increase dairy production, it is necessary to improve the efficiency of the dairy sub-sector for sustainability and profitability. One of the possible ways to do this, is to embrace appropriate breeding techniques (Mutembei et al., 2015).

The annual general beef production is estimated to be 528,990 metric tonnes in the country; two-third of this is mainly supplied by the pastoralists in the ASALs, while the rest comes from the neighbouring countries of Ethiopia, Tanzania, Somalia, and Uganda to meet the deficit (KIPPRA, 2018). Beef sub-sector is very crucial in alleviating poverty in the ASALs. Meat is a vital livestock product and main food for the population in the ASALs. The demand for beef has increased and consumers prefer high quality beef characterized by delicious taste, tenderness and consistency in supply. The number of cattle slaughtered rose by 7.4% from 2,590 thousand heads in 2017 to 2,782 thousand in 2018 (KNBS, 2019). It is only through adoption of breeding technologies that producers can be able to meet the consumer's preferences for both quality and quantity. For instance, adoption of better technologies allows farmers to improve their livestock genetics (Elliott, 2013).

The indigenous cattle constitute about 70% of entire cow population with Small East African Zebu (SEAZ) takes the majority share among all the indigenous cattle (Magotsi and Adan 2019). They are found in virtually all agro-ecological zones but with higher concentration in ASALs. Compared to exotic cattle breeds, they are generally more adapted to the harsh conditions that characterize the ASALs. This makes them the major source of livelihood in such regions.

The SEAZs have not received much formal genetic enhancement and conservation attention. Hence, the breeding initiative for SEAZ has generally been left under the control of the resource-limited pastoralists in the ASALs. This has resulted in inferior genotypes due to inbreeding. It is estimated that a Zebu cattle produces 900 litres of milk on average per year. This is half of what its calf consumes while the crossbreeds produce 1,500 litres annually. Even the average meat output of the adult SEAZ cow is much lower than that of crossbreeds; 200 kilograms compared to 300 kilograms (Kwach, 2018).

There are two major breeding systems commonly used in the developing countries; natural breeding which can either be controlled or uncontrolled and artificial insemination (AI) breeding system. This study focused on AI since it is the proven reliable and convenient breeding system popularly used in upgrading of underperforming breeds worldwide (Kaaya et al., 2005; Tefera et al., 2014). The key players in the Kenya breeding services includes the Kenya animal genetic resource centre (KAGRC), the registered AI services providers, the department of veterinary services and progressive farmers, the Kenya livestock breeders organization who involved in registration of livestock breeders and the livestock recording centre which is tasked with the implementation of the progeny testing programme which ranks AI bulls in order of genetic merits. The semen used by smallholders is either locally manufactured by the KAGRC or imported from fourteen firms from as far as United of America, Australia, New Zealand, South Africa, Spain, Canada, United Kingdom, Italy, France, Denmark, Brazil, Netherlands, Israel. Kenya imported approximately 350,000 units of semen annually. The imported semen is inspected by the Director of Veterinary Service before they are allowed in. The KAGRC has more than 100 bulls and through its 42 appointed agents distributed about 45,000 monthly or 650,000 units annually. The Agricultural Development Corporation (ADC) in Kitale also manufactures and distributes semen through various agents. The smallholder livestock farmers can access the AI services from different providers such as veterinarians, agrovets and trained AI technicians and milk cooperatives.

For the SEAZ to contribute to the improvement of efficiency and competitiveness of the livestock sector in the ASALs of Kenya, optimization of breeding programmes by use of modern breeding strategies such as AI is necessary.

The poor livestock performance in the ASALs necessitates upgrading of the SEAZ through AI. In this way, the germplasm of the bull with the traits of economic interest can be successfully utilized by numerous farmers on many cows. With AI, a mature bull produces over 10,000 offsprings annually (EADD, 2011) and this reduces the economic burden of keeping live bulls as well as reducing the chances of spreading diseases in the herds if natural breeding is used.

1.2 Statement of the Research Problem

Through AI technology, Kenya was able to improve and increase their dairy cattle herd from approximately 300,000 in the mid-1960s to about 4,316,153 in 2014 (ERA, 2015; Lawrence et al., 2015). However, due to high rate of poverty in the ASALs, indigenous livestock farmers are not able to exploit the available technologies. Nationally, the proportion of population living below the overall poverty line is 36.1%. The poverty headcount rate in Kajiado and Makueni was estimated to be 40 and 34%, respectively from 2015/2016 period (KNBS, 2018b).

Although, both the national government and non-governmental organizations have been in the forefront in advocating for the adoption of AI as a mean of upgrading the SEAZ in drylands of Kenya, the uptake of AI is still low. Previous studies have revealed that a considerable number of smallholder farmers are using natural breeding service despite the advantages associated with AI technology. In spite of noteworthy increment in the accessibility of AI service providers for the last ten years, its applicability is still very low in Kenya (Lawrence et al., 2015; Kebebe et al., 2017).

Baltenweck et al. (2004) noted that, about 81% of the smallholder farmers used bull service in spite of the fact that they are aware of AI. Lawrence et al. (2015) found that most farmers were aware of AI, but only 16% of the sampled population had used the technology. Kebebe et al. (2017) found that less than half and fewer than 10% of sampled farmers in Kenya and Ethiopia respectively adopted the improved dairy technologies.

Considering the potential of AI technology in improving livestock productivity, its low usage since its introduction in Kenya in 1945 has negative impacts on dairy and beef sub-sector development. It is therefore, essential to analyse the low uptake of AI technique in the drylands of Kenya. Several studies have been done on the adoption of AI by smallholder dairy farmers in the high potential areas (see for example Makokha, 2006; Lawrence et al., 2015, Kebebe et al., 2017). However, little research has been done in low potential areas where local breeds are in abundance (for instance Khainga et al. 2015 & 2018). Therefore, this study contributes to address the knowledge gap by assessing this level of uptake of AI by livestock farmers across the nomadic and agro-pastoral production systems in Kenya's ASALs.

1.3 Research Objectives

The purpose of this study was to contribute insights for improving livestock production in ASALs of Kenya by assessing factors that influence adoption of AI in Kajiado and Makueni Counties. The specific objectives were to:

i Characterize livestock farmers and breeding services

ii Analyse factors affecting smallholder livestock farmers' decisions to adopt AI services

iii Assess determinants of the intensity of AI adoption

1.4 Research Hypotheses

i. There is no statistically significant difference between the mean number of adopters and non-adopters of AI services in Kajiado and Makueni Counties.

ii. Socio-economic and institutional factors have no influence on the livestock farmers' decision to adopt AI.

iii. Technology characteristics, socio-economic and institutional factors do not affect the intensity of AI adoption.

1.5 Justification of the Study

The study aims at increasing livestock productivity in a bid to alleviate poverty and improve welfare among the poor rural smallholder livestock farmers in the ASALs. Therefore, characterizing the AI adoption was vital to the livestock farmers who will use the results to improve their adoption levels in order to increase their production. The findings on characterization of AI adoption are also useful to Makueni County government since they are in line with the county integrated development strategy number five on livestock development which aims at increasing livestock production by embracing adoption of new agricultural technologies (CIDP, 2018-2022a, *p*11). These insights are also helpful to the County government of Kajiado as per their strategic development priority number 4.4.3, which targets economic pillar, on agriculture, livestock, fisheries and cooperative development. The County is committed to increase livestock production through increasing the adoption of appropriate agricultural technologies (CIDP, 2018-2022b, *p*92-94).

The AI is a very vital technology for improving dairy and beef production. Therefore, analysing factors that hinder its adoption is a worthwhile venture. This information is useful to breeders to develop cattle breeds that suit the needs of the farmers and are in line with Makueni County governments CIDP strategy number five on dairy development to enhance the AI programme (CIDP, 2018-2022a, *p*11). It is also in line with Kajiado County's economic pillar number 4.4.3 on agriculture, livestock, fisheries and cooperative development (CIDP, 2018-2022b, *p*92-94). The findings are in line with the United Nations SDG number one with aims to ending poverty in all its forms everywhere and goal two of zero hunger, achieving food security and improved nutrition and promoting sustainable agriculture (UN, 2019).

1.6 Study Area

The study was conducted in Kajiado and Makueni Counties (Figure 1). Kajiado County is primarily a nomadic pastoralist rangeland where most of the farmers derive their livelihoods from the livestock. This sub-sector is a priority for the county government of Kajiado as per their strategic development goal number 4.4.3, which targets improvement in agriculture, livestock, and fisheries. The County is committed to increase livestock production through embracing the adoption of appropriate agricultural technologies such as AI (CIDP, 2018-2022b, *p*92-94).

The county had a population of 1,117,840 persons as per national census of 2019. The County had about 157,302 dairy and 525,290 beef cattle (KNBS, 2017a). The average annual milk production is 912721 litres and beef production are 6639 tonnes per year (CIDP 2018-2022; *p*32). The poverty headcount rate in Kajiado county stand at 40% from 2015/2016 period (KNBS, 2018b). The poverty and hunger situation are aggravated by frequent droughts and limited adoption of livestock improvement technologies.

Makueni County is one of the ASALs, which is dominated by agro-pastoralism production system. It has an average temperature range between 15C – 26C and annual rainfall ranges between 250mm to 400mm per annum on the lower regions of the county and the higher region receives rainfall ranging from 800mm to 900mm. The county has a population of 987,653 persons as per 2019 census.

The agro-pastoralists are sedentary, they mainly keep livestock and cultivate various crops alongside. They are fairly commercialised compared to nomadic pastoralists. There is a total of 258,181 local breeds in Makueni County (KNBS, 2017b). Livestock production is priority value chain for the county as stipulated by the county integrated development strategy number five on livestock development which aims at increasing livestock production by embracing adoption of new agricultural technologies (CIDP, 2018-2022a; *p*11). The poverty headcount rate in Makueni stand at 34% from 2015/2016 period (KNBS, 2018b). The county experiences many challenges which range from inadequate rainfall, drought and frequent parasites and diseases outbreak which result into loss of livelihoods. These natural calamities trap the vulnerable communities in Makueni in perpetual poverty.

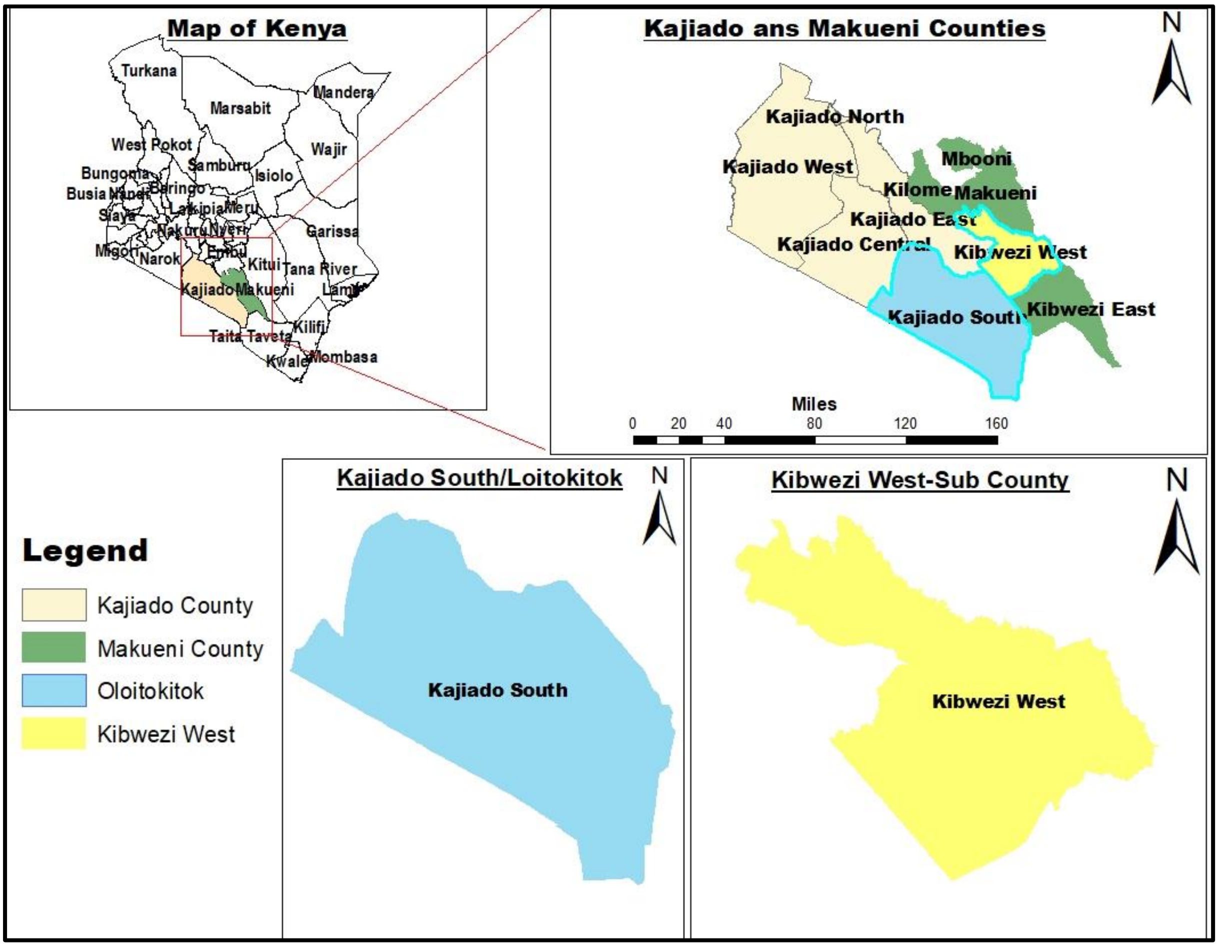

Figure 1: Map of study sites in Kajiado and Makueni Counties
Source: KNBS (2017).

1.7 Organization of the Thesis

This thesis is organized into five chapters. The first chapter introduced the background, research problem, objectives and hypotheses of the study. Chapter two provides a review of the relevant literature. The research methodology comprising conceptual and theoretical frameworks, sampling procedure, data collection method and empirical analysis are described in chapter three. The results are presented and discussed in chapter four. Finally, the conclusion and recommendations are offered in chapter five.

CHAPTER TWO: LITERATURE REVIEW

2.1 Overview of the Global Dairy Industry

The world milk output in 2018 was estimated to be 843 million tonnes. This was an increment of 2.2% from 2017, attributed to production expansion in Turkey, Pakistan, Argentina, European Union (EU), India and the United States of America (USA) (Figure 2). The increment was mainly attributed to increase in dairy herd numbers coupled with improvements to milk collection processes in Pakistan and China, increased yields per cow in Europe and USA, efficiency improvement in integrated dairy production systems in Turkey, and utilization of idle land capacity as well as increased demand from the processing sector and imports in Argentina (FAO, 2019).

The global dairy products trade increased to 75 million tonnes from 72.8 million tonnes in 2016, equivalent to 2.9% increment from 2017. The biggest contributions for export expansion in the year 2018 came from North America (28.7%), South America (27.2%), Central America and the Caribbean (15.2%). Export increment in Asia was 0.9% and that of Oceania was 0.6%, but in contrast, Africa's exports declined by 4.8% due to bad weather and insecurity in many sub-Sahara African countries (FAO, 2019).

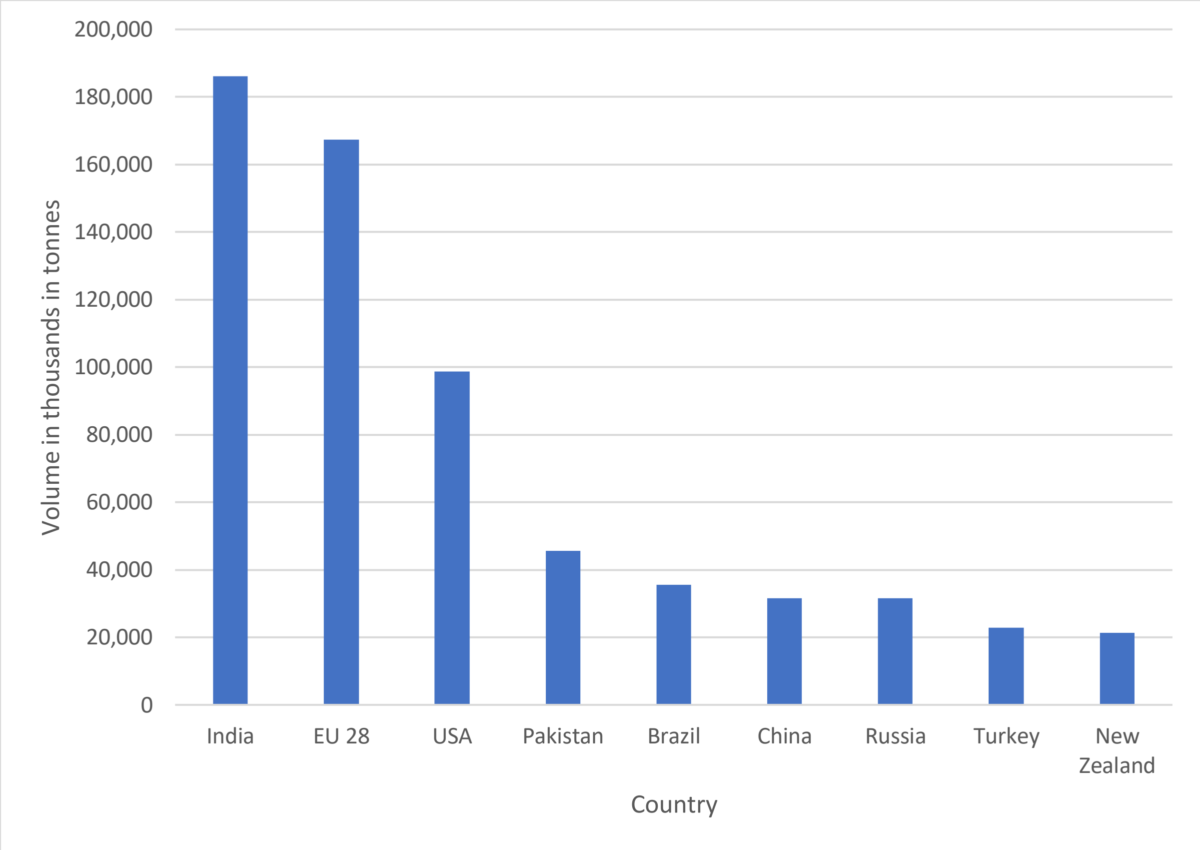

Figure 2: World milk production

Source: FAO (2019).

In Africa, the milk output increment was approximated to be 1.1% on account of output in some big milk producing countries such as South Africa, Kenya, Morocco and Algeria, but partly offset by decreases elsewhere, especially in Niger and Mali. The increment in milk output in Kenya was attributed to good weather and various government support initiatives such as the introduction of school milk programme. In South Africa, the expansion of milk output was consistent for two consecutive years (2017and 2018) (FAO, 2019).

Kenya's dairy subsector is one of the biggest industries in the agricultural sector, ahead of tea. The importance of dairy subsector in Kenya is manifested by a number of factors such as; an estimated 1.8 million smallholders' dairy farmers derives livelihoods from dairy farming and more than 700,000 people are employed directly in milk value chain (MoALF, 2019).

The Kenyan milk production is one-sixth of the 18% produced in Sub Saharan Africa (Odero-Waitituh, 2017).

The milk production is projected to increase by between 4.5% and 5 % yearly in the next decade and by the year 2030, it is projected that the yearly dairy production in Kenya will grow to about 12 billion litres (MoALF, 2019).

Kenya and South Africa are the only two Countries in Africa that produces enough milk for both domestic consumption and export. The dairy cattle reared are exotic breeds, crosses between exotic and local breeds in Kenya. Milk production in Kenya is mainly a smallholder farmers enterprise with recent assessments indicating that small scale producers supply more than 70% of the milk (KIPPRA, 2018).

Kenyan milk production systems comprised of two main systems: small-scale and large-scale system. Dairy production is dominated by the smallholder farmers. The difference between the two production systems are in use of inputs, sizes of operation, and level of management. Small-scale farmers feed their dairy cattle mainly from forage and very small quantities of concentrate, but some smallholder dairy farmers are highly commercialized and well versed in dairy production, with high-quality management, while dairy cattle under large-scale are kept under intensive production system and are highly commercialized (MoA, 2017).

Despite the determination and zeal of smallholder dairy farmers in production, they are constrained by inadequate and un-reliable information on milk market outlets , low quantity and quality of feeds, limited access to veterinary and AI services, low technical skills on production, lack of collateral for loans, high cost of production , poor rural infrastructure and lack of storage facilities leading to milk spoilage and loss at the farm level.

Kenya’s milk processing has been dominated over the past few years by five major processors namely; Brookside Dairy Limited (38%), New Kenya Cooperative Creameries (23%), Githunguri Dairy Farmers Cooperative Society (14%), Sammer group (4%) and Buzeki Dairy (4%). These processors have established cooling stations strategically within their targeted raw milk collection areas. Milk production fluctuates across the seasons because the yield depends on weather. During peak production seasons, the processors lack the capacity to fully absorb all the milk availed but the situation changes during dry spells when production diminishes and most processors' production capacity remains idle (KIPPRA, 2018).

.

2.2 Overview of the Global Beef Industry

Beef is a vital food for many people in the world; it is a rich source of protein with varying amounts of fat. It is a high-quality animal protein containing all the necessary amino acids which are important for the growth and maintenance of the human body by repairing and building new muscle tissues (Maina et al., 2018).

The three main beef producers accounting for 47% of the world's beef supply are USA (20%), Brazil (15%) and the EU (12%) (Figure 3).

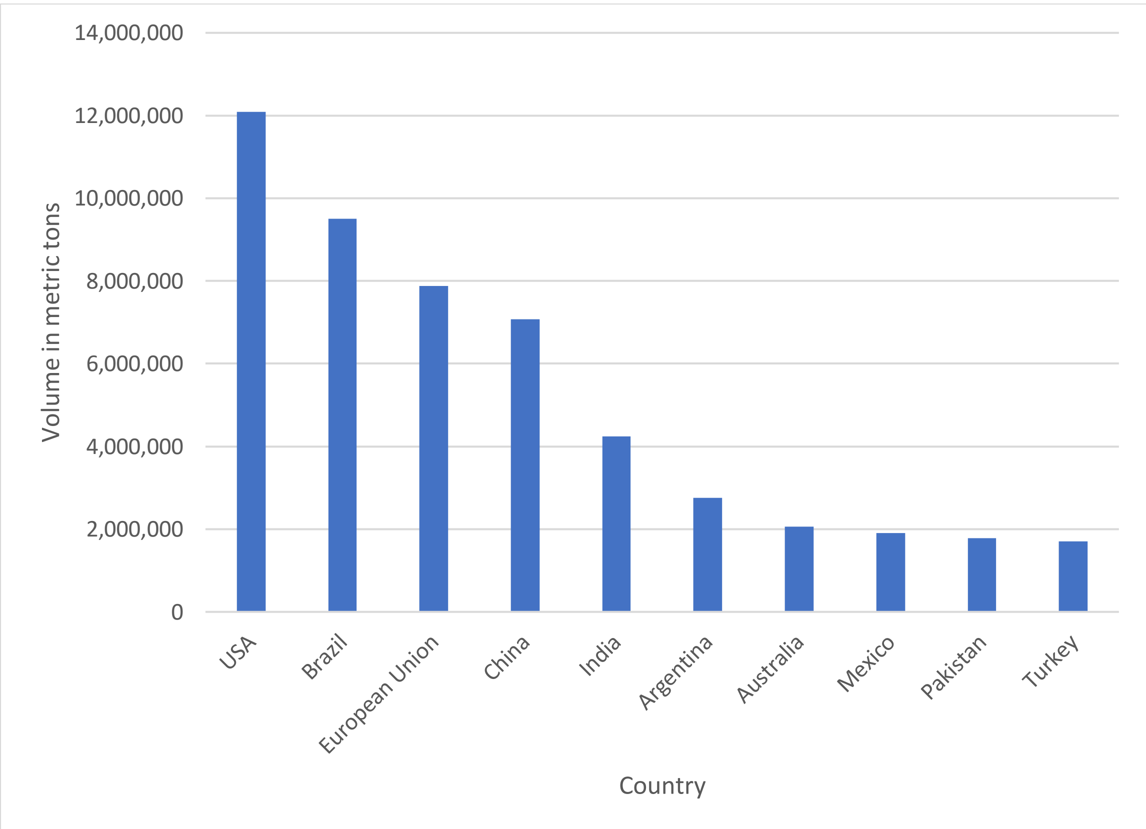

Figure 3: Major beef producers in the world

Source: FAS/USDA (2017).

The world beef production projection for 2020 is marginally revised downwards from the prior projection due to world economic disruptions caused by coronavirus pandemic which has suppressed beef demand and supply. The world beef output/production in 2020 was also expected to decrease slightly due to herd rebuilding in Australia mostly offset by growth in Brazil, China and North America. As such, the world beef trade forecast is expected to decrease in coming year post-covid-19.

In the current year, 2020, world beef market is expected to decrease by 2% as global economic growth is adversely affected by coronavirus. The consumers are expected to change their eating habits and switch to less expensive proteins. The hard hit and depressed restaurant traffic arising from prolonged lockdowns and restriction on outdoor eating are also expected to negatively impact beef demand because a great proportion of world beef's consumption takes place in the hotels, restaurants, and other institutions sector (USDA, 2020).

The world's largest beef-consuming countries are the USA, Brazil and China. The global beef consumption was initially projected to increase gradually over the next decade. Specifically, it was anticipated that, by 2027, the global beef consumption would be 8% and 21% higher than in 2018 in developed and developing countries respectively. In per capita terms, beef consumption in the developing world would remain low relative to developed countries, at about one-third in volume terms. Increased beef consumption level is also expected in Turkey, Viet Nam and Kazakhstan. The result is an expected 24% increase in beef consumed in Asia over the next ten years (USDA, 2019); but these might change in the reverse direction as the effects of covid-19 become more clearer on various value chains in the world.

The global meat trade was 31 metric tonnes higher in 2017 than in 2016, which translate to 1.5% higher. The global trade increased in bovine meat by 4.7%. The slow growth in world meat trade in 2017 compared to 2016 was because of reduction in meat's import volumes by China, Egypt, the EU, Saudi Arabia, Turkey and the USA (USDA, 2019).

As shown in Figure 4, the top five beef producers in Africa are the South Africa, Egypt, Algeria, Angola and Congo (USDA, 2019).

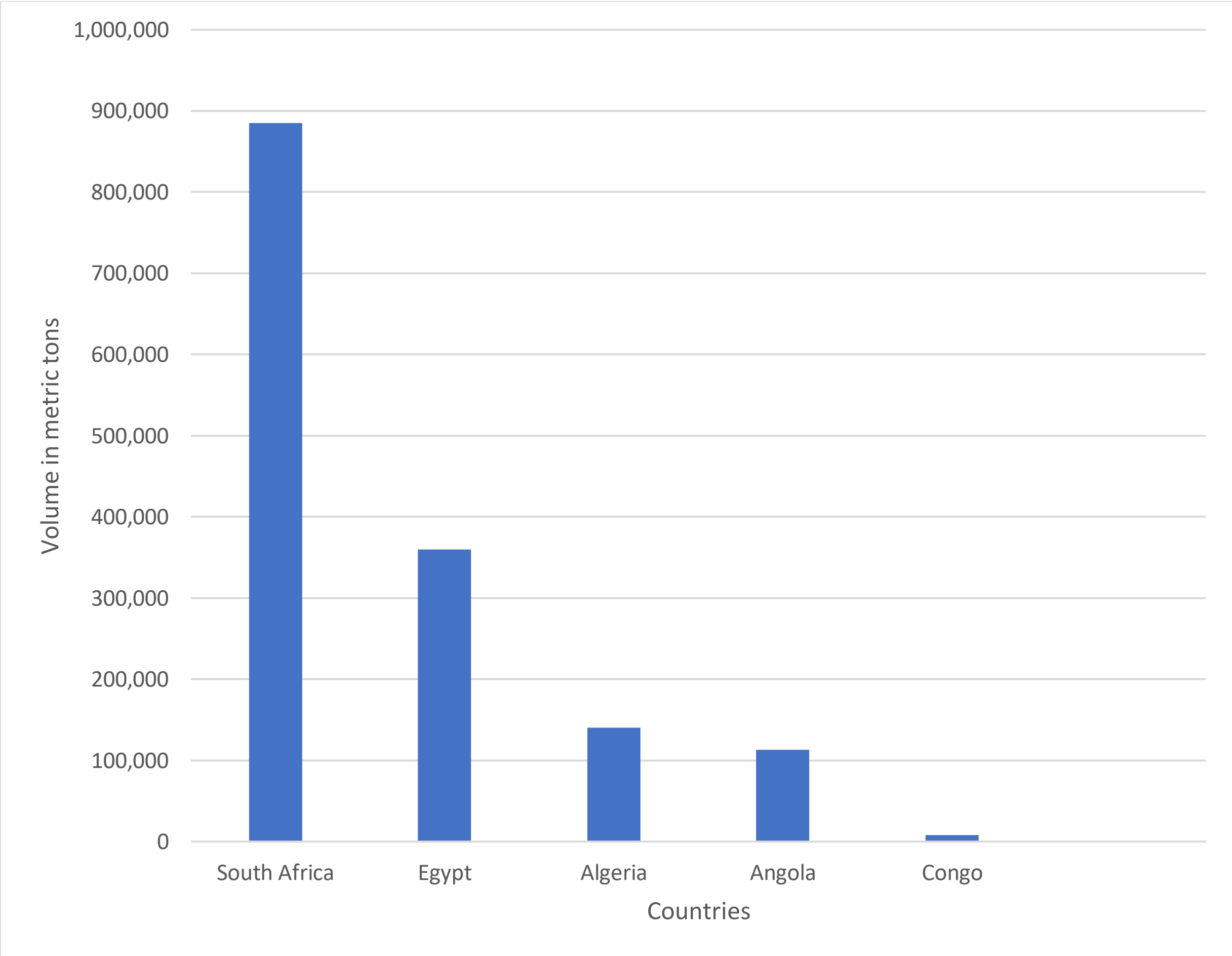

Figure 4: Top five beef producing countries in Africa

Source: FAS/USDA (2017).

Beef production in Kenya is dated back to pre-independence. Before the missionaries, the native Africans kept the indigenous SEAZ mainly under traditional systems of production for meat and dairy. It was predominately practiced in the Rift Valley and North eastern Kenya where nomadic pastoralists were the majority although some communities in Western, Nyanza and Central also were involved in SEAZ rearing. The colonial settlers came with the exotic cattle breed; however, the Africans were confined to their pastoralist system of production until the Swynnerton plan of 1954, which permitted Africans to keep exotic breeds (MoALF, 2019).

Beef production in Kenya is mainly for domestic consumption. The beef industry is one of the promising subsectors within the agricultural sector accelerated by population growth, income and export. The population of beef cattle in Kenya is 13,495,692; 70% being under nomadic pastoralists and agro-pastoralists in the ASALs while; the rest are kept under intensive production such as ranches (ERA, 2015). About 70% of annual beef output is mainly from Zebu cattle population found in the ASALs while the rest is from culls from the dairy herd (MoALF, 2019).

The SEAZ cattle is resistant to harsh climatic conditions of ASALs and is also tolerant to parasites and diseases. Further, it achieves the normal calving interval of 365 days and if fed well, its crossbreed produces a good mature weight of 300kg. These characteristics have made it popular than the other beef cattle types in Kenya's ASALs (Kwach, 2018). The production of beef is mainly pasture-based in Kenya, which depends on land availability. Beef marketing is dominated by Kenya Meat Commission (KMC). The main slaughterhouses are located in Darogetti, Miritini, Eldoret, and Nakuru. However, the KMC has been plagued by prolonged mismanagement and operational inefficiencies over the years rendering it insolvent and persistently relying on government bailouts, yet failing to utilize its processing capacity.

2.3 Empirical Literature on Adoption

Many adoption studies have been done on crops (see for example Pierpaoli et al., 2013; Abadi et al., 2015; Tegegne, 2017; Ongoche et al., 2017; Atnafe et al., 2018) and in livestock (Otieno et al., 2013; Tefera et al., 2014; Mutembei et al., 2015; Khainga et al., 2015). They grouped factors affecting technology adoption into human characteristics such as age, and education level, financial and structural attributes including debt and asset, off-farm income, farm size, and labour, and institutional attributes like access to extension service and credit.

In the analysis of the decision to adopt agricultural innovations, the household's economic status is often associated with farmers' behaviour with respect to farmer attributes, endowment, information asymmetry, uncertainty, risk, institutional vacuum, availability of production inputs, infrastructure, and income (Rogers, 2003; Uaiene, 2009). Recent studies included a social aspect in the groups of factors influencing technology adoption decision by farmers (Guye and Sori, 2020).

Some studies classified these attributes into distinct groups. For instance, Akudugu et al. (2012) put factors influencing new technology adoption decision by farmers into three groups; institutional, social and economic attributes. However, this study grouped these factors into three categories; farmers characteristics, institutional variables and technology aspects to suit the farmers' attributes in the area of study.

2.3.1 Farmer Characteristics

Various characteristics have been shown to influence their adoption decisions (see for example, Bonabana- Wabbi, 2002; Keelan et al., 2009; Fernandez-Cornejo et al., 2007; Lavison, 2013; Obisesan ,2014). Howley (2012) observed that all the farmer characteristics positively affect the decision to adopt AI.

Also, family size, income, education level, and group membership positively influence the decision to adopt (Temba, 2011; Tefera et al., 2014' Khainga et al., 2018). The efficacy of AI and education have significant effects on the extent of AI adoption, while experience and age negatively influence the extent of AI adoption.

Other studies such as Mignouna et al. (2011), Khainga et al. (2015), Bayan (2018) showed that income, education level, farm size, experience in AI, herd size, and good use of social networks significantly influenced farmers' adoption decision while risk perception and distance to market were negatively associated with extent of adoption. Considering that, there are mixed findings on how farmers' characteristics influence the adoption decision; the current study sought to assess the effect of farmers' characteristics to validate these mixed findings.

2.3.2 Institutional Characteristics

Various institutional characteristics such as service availability, access to market information, credit facility and extension services are included in this study. Some studies (such as Temba, 2011; Lawrence et al., 2015; Khainga et al., 2018) noted that access to credit and extension services positively influenced farmers' decision to adopt AI technology. Further, Mujeyi,2009, Namwata et al., 2010 and Temba, 2011 noted that farmers are able to improve their production if they have access to credit facilities and extension service. Also, access to credit, membership to cooperative, access to training and demonstration affected farmers adoption decision and intensity of adoption significantly (Guye and Sori, 2020). In the current study, similar results may be possible because of the fact that both studies focused on smallholder farmers if the farmers have access to the service on equal basis.

2.3.3 Technology Characteristics

The technology attributes include technology complexity, risk perception, cost and the relative advantage of the technology. Attributes of technology are vital in influencing the adoption decision of the farmer. The relative advantage, risk, complexity, and technology attributes significantly impacts their diffusion and adoption (Khanal and Gillespie, 2011; Howley et al., 2012; Loevinsohn et al., 2013). Uptake and sustainability of agricultural technologies is subject to farmers' choice which is always as a result of benefits derived from the new technology in comparison with the existing technology (Hall and Khan, 2002; Mwangi and Kariuki, 2015). According to Doss (2003) and Tey et al. (2017), technology characteristic is a precondition for its adoption. The degree to which a farmer experiment with the technology before adopting it, is very critical. The current study expects the technology attributes to influence the intensity of AI adoption either positively or negatively.

2.4 Review of Adoption Models

Several studies on adoption use different empirical models for instance, logit (Gillespie et al., 2014; Ingabire et al., 2018; Akin-Kara, 2019), probit (Ghimire et al., 2015; Khainga et al., 2015), Tobit (Guye and Sori, 2020) and double-hurdle (Tefera et al., 2014; Kuti, 2015; Njuguna et al., 2017).

Utility maximization is key in farmers decision to adopt a new technology subject to constraints (Feder et al., 1985). Some of adoptions of new technologies are in two-tier stages: the decision to either adopt or not and how much of the new technology to adopt (Mercer and Pattanayak, 2003). If the two decisions are made jointly or are determined by the same set of factors, then

Tobit model is appropriate to assess factors affecting farmers' decision to adopt and the extent of technology adoption (Greene, 2007). For this study, Tobit model is not appropriate because it assumed that zero observations are because of economic factors alone but it could be because of farmer unwillingness to participate in the adoption of new technologies for non-economic reasons (Cragg, 1971).

The farmers' decision to adopt new technology precedes the decision on the how much of the new technology to use, and the factors influencing every decision may not be the same (Tefera et al., 2014; Gebremedhin and Swinton, 2003) as assumed in this study. For this case, it is more appropriate to use a 'double-hurdle' model in which a probit regression on adoption (using all observations) is followed by a truncated regression on the non-zero observations.

Among the sampled farmers, some uses technology and others did not use. Also, there exist differences in level of adoption among the smallholder livestock farmers. Some of the adopters fully participated in the adoption of AI whereas some are not. The application of Cragg's double-hurdle model for analysing adoption decisions and intensity of adoption is common in agricultural economics literature (Teklewold et al., 2006; Shiferaw et al., 2008; Gebregziabher and Holden, 2011).

Another alternative approach is Heckman selection model. According to Jones (1989), the vital distinction between the two models is about the sources of zeros. In the Heckman model, the zero observations/non-adopters will never adopt under any circumstance. On the other hand, in Cragg's model, non-adopters are considered as a corner solution in a utility-maximizing model. In the case of AI technology, the assumption of Heckman is restrictive. Since change in AI prices and access to extension services may encourage non-adopters to adopt. Hence, Cragg's double-hurdle model is used in this study instead of Heckman's model.

The double-hurdle model is a parametric generalization of Tobit model. According to Cragg (1971), adoption is a process with two stages/tiers; first is whether or not to adopt the technology, and second is to what extent to adopt. It was assumed in this study that, the decision to adopt the technology and to what level were made independent of each other. The dependent variable in the first stage is the livestock farmers' decision to adopt AI or not to adopt. The decision is binary taking the value of 1 if the decision to adopt AI is yes and zero when the decision is no. Some independent variables maybe included in both equations or in one. Each hurdle is conditioned by the household's socioeconomic characteristics and institutional support service variable or even the technological attributes. Since the dependent variables are difference in the two stages of double-hurdle, then some independent variables may appear in both or not but the most importance thing to note is that, the variables appearing in both stages may have opposite effects or in some cases they may not (Moffat, 2005; Mal et al., 2012; Njuguna et al., 2017). The double-hurdle allows that the two decisions are affected by different set of variables (Tefera et al., 2014).

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Conceptual Framework

The conceptual framework was adapted from Department for International Development (DFID,1999) based on the fact that the population living in the ASALs face many challenges making them vulnerable to food insecurity. These challenges are illustrated in Figure 5.

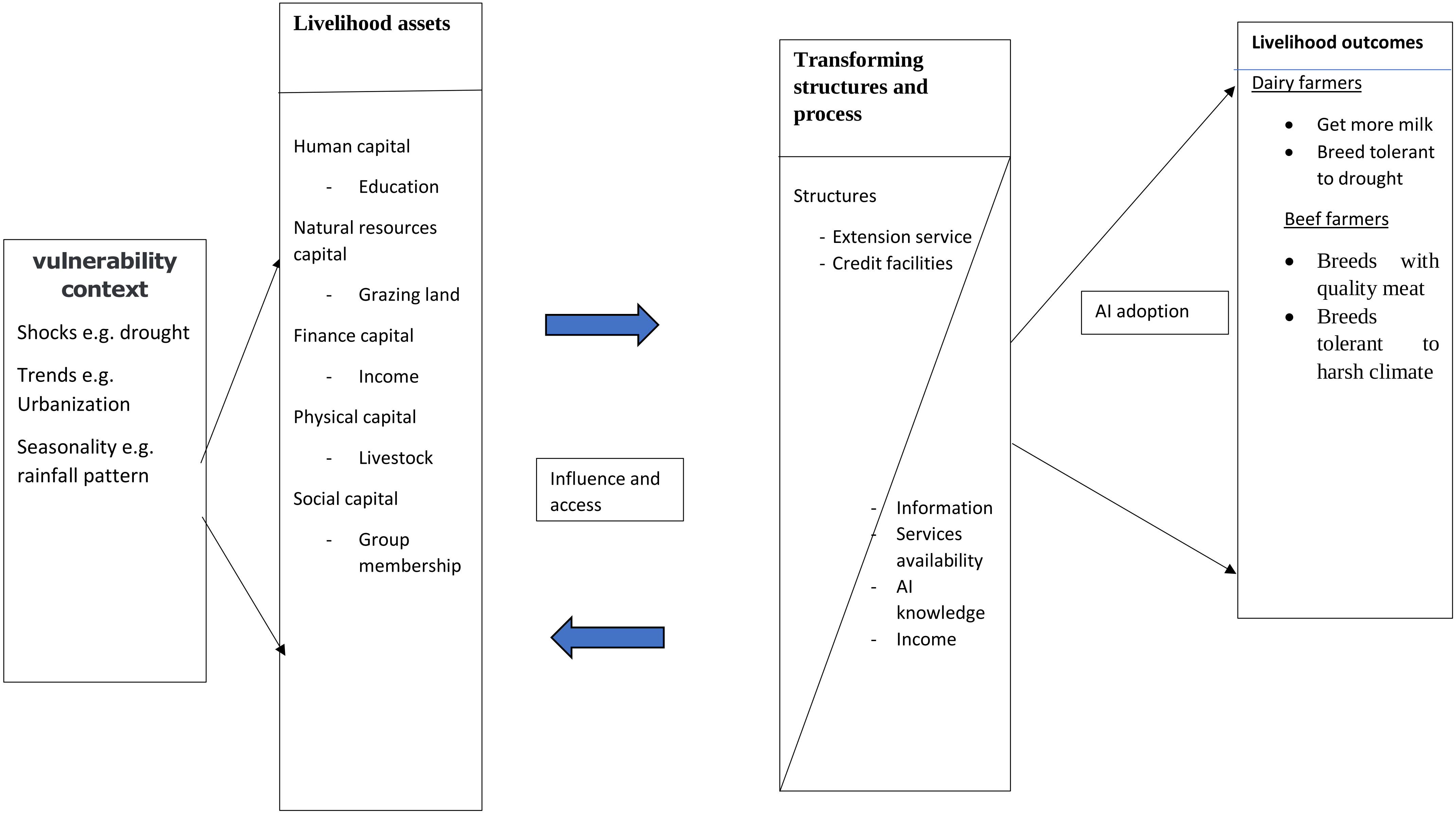

Figure 5: Framework for understanding situational context in Kajiado and Makueni Counties

Source: Adapted from DFID (1999).

In the first box, is the vulnerability context in which Kajiado and Makueni are located. The context is prone to shocks. In Makueni and Kajiado contextual vulnerabilities are aggravated by several shocks such as frequent drought, livestock parasites and diseases (Muriuki, 2012). The shocks result in the losses in form of livestock death and reduced output therefore, keeping the some of the population living there wallowing in abject poverty (NDMA, 2016).

The trends evidenced in Kajiado and Makueni are urbanization, which shrank the grazing land making open grazing almost impossible, land tenure system, which led to land privatization and lastly technology, and the recent introduction of standard gauge railway (SGR) which acts as barrier to access to some places is one notable example. All these culminate into reduced land for grazing for their livestock, which eventually lead to reduced productivity. The seasonality in Kajiado and Makueni is compounded with inadequate rainfall, scarce pastures for their livestock and the fluctuation in market prices for the basic commodities. All these traps the communities living in the ASALs into poverty.

The livelihood asset comprises; the human capital which includes education, experience in livestock keeping and AI, natural resources capital; includes grazing land and land owned, financial capital; includes income and access to credit, physical capital; includes livestock, and shelters while social capital include group membership and trust/mistrust. All these, are scarce in the ASALs and there is a need to strengthen these livelihood assets to help them get out of vicious poverty cycle and to be resilient enough to withstand the unexpected natural calamities.

Transforming, structures and process are embodied in the institutions that are the enablers of adoption of AI technology. This includes the access to extension services, AI service availability, access to credit facilities, information availability, risk perception and the cost of AI services. The availability of these institutional support facilitates the adoption of new agricultural technologies in the rural areas and contribute to improved livestock output (Muriuki, 2012).

If a farmer adopted the AI services, their livelihoods are expected to improve through; breeds which produce more milk, are resistant to bad weather, have short calving intervals and are tolerant to parasites and diseases. Additionally, beef farmers will have breeds with more slaughter weight, and provide quality meat.

3.2 Theoretical Framework

3.2.1 Analysis of Adoption Decisions

The farmers' decision to adopt new technology (AI) is based on the objective of utility maximization (Rahm and Huffman, 1984). The preference for a technology is subject to non-observable underlying utility function. For this study, the number of potential benefits expected from adoption of AI technology include improved productivity output such as more milk and better weight for dairy and beef cattle respectively. However, farmers do not adopt new technology at once because, the decision of each household is affected by many challenges (Sadoulet and de Janvry, 1995). In the case of Kajiado and Makueni, frequent droughts, recurring parasites and disease outbreaks, inadequate veterinary and extension services in the area are some of problems that guide the behaviours of farmers in regards to new technology adoption.

This study was anchored on random utility model (RUM). Based on RUM, a rational farmer will choose a particular technology to maximize welfare. For instance, assume two technologies,T_1 and T_2 with associated utilities U_1 and U_2, where U_2>U_1. Based on RUM, a rational farmer will adopt T_2 instead of T_1 if T_2 has a higher utility associated with it than the alternative T_1.

Following Greene, (2008), let Ui^A represent the utility accruing to household from adopting a new technology such as AI service and Ui^{NA} represent the utility from non-adoption.

The utility accruing to a household can be represented as a linear sum of two components.

$Ui = B^i X_i + \varepsilon_i$ …………………………………………………………………………. (1)

where $B^i x_i$ is the deterministic part of utility that is hypothesized as a function of exogenous variables (x_i) which include household's characteristics, technology attributes and the average exogenous effect on adoption decision by respondents (Walton et al., 2010), and ε_i represents the unobservable/stochastic components of the utility function. Because the household's utility U_i is unobservable, the adoption decision is observed only when an underlying latent variable Y exceeds a given threshold (Wooldridge, 2010). Based on the RUM, the farmer adopts a new technology if $y^* > {}^{\gamma}$ where y is a threshold.

Representing the adoption decision of the i^{th} household as $\mathbf{Y_i}$

.

$\mathbf{Y_i}$ = 1 if $y^* > {}^{\gamma}$ in which case adoption is observed……………………………………….. (2)
and

$\mathbf{Y_i}$ = 0 if $y^* >$ α where non-adoption is observed ………………………………………….. (3)
This gives a model with, a binary dependent variable

3.2.2 Intensity of Adoption

According to Cragg (1971), adoption is modelled as a two-tier process; decision to adopt or not to adopt the new technology and the extent of adoption. The assumption underlying this study was that the decision to adopt AI and the intensity of adoption were made in two different steps.

The two tiers in the Cragg formula are as follows;

$D^*_i = \alpha Z_i + V_i$…………………………………………………………………………….. (4)

$Y^*_i = \beta X_i + U_i$ ……………………………………………….. (5)

where $D^*_i = \{1, \text{ if } D^*_i > 0; 0 \text{ if } D^*_i \leq 0\}$ and $Y_i = \{Y^*, \text{ if } Y_i > 0 \text{ and } D^*_i > 0; 0, \text{ if otherwise}\}$ D^*_i =latent variable that takes the value of 1 if the farmer adopts AI technology; 0 otherwise, Z_i= vector of household characteristics explaining level of adoption; X_i- represent a vector of independent variables explaining the intensity of adoption; U_i and V_i– are stochastic terms which are assumed to be independent.

3.3 Empirical Data Analysis

3.3.1 Characterization of Livestock Production in Kajiado and Makueni Counties

Descriptive statistics such as percentages, frequencies, mean and standard deviations were used to provide a summary of farm and farmer characteristics. Independent t-tests were computed to determine statistical differences between the means of AI adopters and non-adopters with respect to continuous variables such as access to extension and information services.

3.3.2 Analysis of Factors Influencing the Adoption and Intensity of AI adoption

Considering that a farmer’s decision to adopt AI precedes the decision on the intensity of AI use, and that the factors hindering every decision may not be the same, the double-hurdle' model was deemed appropriate in this study. Following Cragg, (1971), the probit regression was first estimated on the adoption for all the respondents and subsequently, a truncated regression on the non-zero observations. This approach overcomes the key shortcoming of the alternative Tobit model which assumes the zero observations are due to economic factors alone whereas, they could be because of the farmers' unwillingness to participate in technology choice for non-economic reasons.

The first hurdle on adoption decision was estimated through a probit regression given as (Moffat, 2005):

$$\left.\begin{array}{l} D_i = 1 \text{ if } D_i^*>0 \\ D_i = 0 \text{ if } d_i^* \leq 0 \end{array}\right\} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

$$D_i^*=\alpha^1 z_i^*+ui$$

where, D^* was the latent variables which take 1 if the decision to adopt AI technology was yes and 0 for not adopting AI, α was the vector of parameters to be estimated, u_i was error term, and Z_i was vector of household characteristics.

The second hurdle gives the outcome equation, in which a truncated regression was applied to assess the intensity of AI's adoption. The respondents' observations which indicate positive use of AI were vital in this hurdle. The truncated regression model was fitted as follows;

$$Y_i = Y_i^* \text{ if } Y_i^*>0 \text{ and } D_i^* >0$$

$$Y_1= 0 \text{ otherwise} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

$$Y_i^*= \beta^1 X_1+v_1$$

where, Y^* was the number of livestock bred from AI technology, X_i were independent variables, β was vector of parameters and v_i was the error term.

The distributions of error terms were as below:

$$\left.\begin{array}{l} U_i \text{ ----N } (0.1) \\ V_i \text{---N } (0_1 0^2) \end{array}\right\} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

The error terms u_i and v_i in this study were assumed to be independently and normally distributed.

It was assumed that farmers' decision on the adoption and intensity are separately/independently made. The double-hurdle regression on observed variable was specified as follows;

$$Y_i = D_i Y_i^* \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (9)$$

The log likelihood function for the double-hurdle regression was as follow:

$$\text{Log L} = \frac{\Sigma}{0} \text{ in } (1 - \phi \alpha Z_i (\frac{\beta Xi1}{\sigma} + \frac{\Sigma}{+} \text{ in } (\phi \alpha Z \frac{1}{\sigma} \phi (\frac{y_i - \beta X_i 1}{\sigma}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots (10)$$

where $\frac{\Sigma}{0}$ was a summation over the zero observation, $\frac{\Sigma}{+}$ was summation over positive observations, $\boldsymbol{\phi}$ was the standard normal cumulative distribution function (multivariate or univariate) and ϕ denotes univariate standard normal probability distribution function. The Z_i, β, α, and σ are as defined earlier stated.

3.4 Description of Variables and their Expected Signs

The variables included in the first step of the analysis are shown in Table 1.

Table 1: Description of variables in the probit model

Variables	Descriptive of variables	Unit of measurement	Expected signs
Dependent variable			
Decision to adopt AI or not			
Independent variables			
Extension visit	Number of extensions visit per year	1 = Yes 2 = No	+
Age	Age of household head	Years	+/-
Education level	Number of years one spent in school	1 = formal education 2= No formal education	+
Gender	Gender of household head	1 = male 2= female	+
Family size	Number of people living together	number	+/-
Access to information	Getting information about AI, market information for the last 12 months	1 = Yes 2= N0	+
Herd size	Number of livestock one owned	Number	+/-
Cattle farm size	Land allocated to cattle in acres	Acres	+/-
Off-farm employment	Total money received per year from off-farm activities	Kenyan shillings	+/-
Distance to market	Distance from respondent home to nearby market	Kilometres	-
Contract market sell	Sale of cattle through prior formal agreement	1 = Yes 2 = No	+/-
Group membership	Member of a developmental group	1 = Yes 2 =No	+/-

The variables included in the second stage of the double hurdle model as shown in Table 2 below.

Table 2: Description of variables in the second tier of the double hurdle model

Variables	Descriptive of the variables	Unit of measurement	Expected signs
Dependent variable			
Proportion of calves bred from AI			
Independent variables			
Distance to AI station	Distance from respondent home to nearby AI centre	Kilometres	+/-
Access to credit	Money from loan agency/group	Kenyan shillings	+/-
Extension visit	Number of extensions visit per year	1 = Yes 2 = No	+
Age	Age of household head	Years	+/-
Education level	Number of years head of household spent in school	1 = formal education 2 = No formal education	+
Gender	Gender of household head	1 = male 2 = female	+/-
Household size	Number of people living together	Number	+/-
Access to information	Getting information about AI, market information for the last 12 months	1 = Yes 2 = No	+
Herd size	Number of livestock one owned	Number	+/-
Cattle farm size	Land allocated to cattle	acres	
Off-farm employment	Total money received per year from off-farm activities	Kenyan shillings	+/-
Distance to market	Distance from respondent home to nearby market	Kilometre	-
Contract market sell	Sale of cattle through prior formal agreement	1 = Yes 2 = No	+/-
Cost of AI	Money paid by farmer to inseminate his/her cow	Kenyan shillings	-
Group membership	Member of a developmental group	1 = Yes 2 = No	+/-
Risk perception	AI technology faulty	1= Yes 2 = No	-
Mistrust /dishonesty	Provision of false information from service provider	1 = Yes 2 = No	-

Education was captured as the number of years that a respondent spent in school. An educated farmer has the ability to analyse the risk and cost associated with the adoption of new technology and be able to interpret it well and use the relevant information to decide to adopt or not (Mignouna et al., 2011; Lavison, 2013). Other studies reported a negative effect of education on farmers' decision to adopt new technology (Samiee et al., 2009).

Age was measured as the number of years of the household head. The relationship of age and adoption of AI and its intensity was expected to be either positive or inverse. Older people are considered to have gained enough experience and therefore are expected to adopt a new technology with higher utility than the younger people (Mignouna et al., 2011). In other studies, age has been found to have a negative effect on the adoption of new technology (Khainga et al., 2015).

Access to credit have a positive effect in increasing agricultural productivity because it allows individual farmer to exploit other factors of production. It is expected to be positive in this study. Most studies revealed lack of credit to be responsible for the low adoption of technologies (Namwata et al., 2010).

Access to extension services was expected to positively affected on the adoption and intensity of AI. The dissemination of information for the new technology has to be supported through the presence of good extension services. The regular contacts between extension agents and farmers increased the chances of farmers to adopt the new technology (Namwata et al.,2010). The extension is understood as an assistant to farmers that enable them to perceive, understand and interpret the production problems.

The family size is referred to as the number of people living together and sharing common meals and shelter. The effect of household size on adoption and intensity of AI adoption was expected to be negative because AI is not labour intensive, therefore, a large household size is not important in the AI adoption process (Tefera et al., 2014).

The effect of off-farm employment relationship on AI adoption was expected to be either positive or negative. Off-farm employment acts as a vital arrangement for overcoming credit challenge faced by the households and a substitute to loan capital in rural economies (Tefera et al., 2014). However, if the nature of off-farm engagement is too time-constraint such that someone cannot invest in other business ventures, the relationship with AI adoption may be negative (Reardon et al., 2007; Diiro, 2013).

Membership in livestock groups enables farmers to share information such as the benefits of new technologies. The relationship of group membership with AI adoption was expected to be either positive or negative (Teferi et al., 2015; Akin-Kara, 2019). Markets are avenues where farmers share their experiences, lessons and information about their products. Distance to open-air market was captured in kilometre from respondent's home to the nearby open-air market. Distance to market was expected to be negative as farmers living near to market are more likely to adopt AI (Teferi et al., 2015).

Access to information on market price and new technologies was expected to positively affect the adoption of AI and its intensity. This is attributed to the fact that, farmers who have access to market information have a high probability to adopt AI technology (Uaiene et al., 2009).

Cattle farm size was captured as the size of land allocated to cows in acres. The relationship between farm size and AI adoption and extent of adoption was expected to be positive. The farm size act as premise for future expansion. The farmers who have large cattle farm size have high probability to adopt AI technology than their counterparts with smaller farm (Mignouna et al, 2011).

Distance to the AI centre was measured as in kilometres. The relationship with the adoption of AI and its intensity was expected to be negative. Farmers who stay near an AI centre are expected to adopt AI due to lower travel time and cost which, in turn reduce the transaction costs in term of searching for the service and information (Idrisa et al., 2012; Murage and Ilatsia, 2011).

The dishonesty/quality of AI was captured as the provision of false information by the service providers. It was captured by asking farmer whether he/she has ever experienced any case where he/she paid for AI service to get improved breed but later on turn out to be of the zebu origin during the calving down. It was expected to be negative. Farmers who have experienced any case of cheating from the service providers are less likely to intensify the adoption of AI technology (Kaaya et al., 2005).

Gender is very vital in influencing adoption of new technologies because head of the household has control over decision making and men which are head of households by default have more access to and control over vital production resources than women due to socio-cultural values and norms (Mignouna et al., 2011). Herd size was captured as number of cattle owned by the household. The relationship between herd size and adoption and intensity of AI adoption was expected to be positive. Households with larger herds are more likely to adopt the AI technology (Kaaya et al., 2005).

Cost of AI technology was measured as the amount of money paid to have a cow inseminated. The relationship was expected to be negative to conform with the law of demand (Kaaya et al., 2005). The complexity of AI technology was captured as how hard to use the technology on your farm. The relationship was expected to be negative (Howley et al., 2012) because complicated technologies are hard to operate, hence discourages farmers to adopt.

Contract market was measured as the formal agreement signed between farmer and buyer of cattle. The relationship was expected to be positive in that farmers with formal agreement with buyers are more likely to adopt and intensify the AI adoption to impress their buyers to hold on to the agreement for longer time.

Risk perception was measured as how much farmers feared to use AI technology because of unforeseen risk. The relationship was expected to be negative in that farmers who does not fear using the AI are more likely to adopt and intensify the adoption of AI on their head (Bayan, 2018).

3.5 Sampling Procedure

The sample size was calculated using Cochran (1963, *p*75) because, the target population was large and the variability in the proportion that is likely to adopt the technology was not known. Hence, it is assumed that the maximum variability ($p = 0.5$). The confidence level was assumed to be 95%. It was difficult to know the variability of population in the study areas because, in Kajiado, the population is largely pastoralists who move seasonally in search for water and pastures for their animals, so, it is hard to find the same person in one place every year. Therefore, it is hard for concern entities to obtain accurate individual information. In Makueni, the population is largely agro-pastoralists and so, not everyone in the community keep livestock. As such, the study was not able to obtain the list of households that owns cattle. The resulting sample size from Cochran's formula is shown below;

$$n = \frac{Z^2pq}{e^2} = 0.9604/0.0025 = 384 \quad \text{.....} \quad (11)$$

where;

n = the calculate sample size,

z^2 = the abscissa of the normal curve; the value of z is obtained from the statistical table representing the area under a normal curve

e = the desired level of precision (taken as 5%),

p = the estimated proportion of an attribute that is present in the population and

q = 1-p.

Multistage sampling procedure was used (Horppila and Peltonon, 1992). In the first stage, Kajiado and Makueni Counties were purposively selected based on the number of indigenous cattle in the counties and the type of production systems practiced; Kajiado being largely nomadic pastoralists and Makueni being the agro-pastoralists.

In the second stage, Loitoktok and Kibwezi west sub counties were selected respectively from the two Counties based on the number livestock kept there. Loitoktok being the large subcounty in Kajiado with large number of pastoralists has about 165011 cattle, which represents 24% of total cattle in the County. In Makueni, Kibwezi west subcounty has high number of indigenous livestock of 64791 cattle, which represents 25% of total cattle in the County (KNBS, 2017b).

In the third stage, six sampling villages were randomly selected from Loitoktok and Kibwezi west (three each from the two sub-counties) and simple random sampling method was used to select the respondents. All the respondents were given equal chance of selection. Since there was no list of the respondents to be interviewed, the first household at entering point who keep cattle became the first respondent because the study only target cattle keepers.

3.6 Data Collection Method

A structured questionnaire (*Appendix 1*) was used to collect the data through primary face to face interviews. The questionnaires were administered with the help of well-trained enumerators. Face-to-face interviews were favoured over the other methods such as telephone call and email because the target population was made of many illiterate people, and the areas lack most of the social amenities such as electricity to run internet, and some of them hardly owned mobile phones to support phone call interviews.

According to Minhat (2015), face to face interviews are useful in exploring experiences perceptions and providing detailed insights required from individual participants. The participants in Makueni were very friendly and the survey team did not encounter any problem there. However, in Kajiado, it was often difficult to find respondents in their homesteads because they took their livestock far-away for grazing as early as 8 am. There were also incidences where some interviewees demanded some monetary compensation or became unresponsive citing time constraints. These challenges were remedied through use of local guides (commonly referred as *nyumba kumi* elders). Additionally, some extra 15 participants were interviewed to cater for potential incomplete questionnaires. Eventually, one questionnaire was dropped during data cleaning due to incomplete information on the variable of interest AI-adoption and the valid sample size became 398.

The questionnaire was structured into six main sections; *section A* captured information on cattle production (type of cattle breed, production systems, grazing system, experience in cattle keeping and use of AI services), while, *section B* had questions on production services (extension, breeding, veterinary, and feed resources), *section C* captured information on household assets and other farm enterprises while*; section D* included questions on institutional support services (credit, markets for inputs and outputs, market information, group membership and contracts), Information on off-farm activities was captured in *section E* and Finally, *section*

F had data on household characteristics such as age, gender, marital status, and level of education.

3.7 Multicollinearity Tests

Multicollinearity in econometrics occurs when there is co-relationship among the explanatory variables used in the models. It leads to large standard errors, large confidence intervals and unreliable statistical inferences. The variance inflation factor (VIF) method was applied to check for multicollinearity. To compute the VIF, an ordinary least square (OLS) regression was estimated and VIF was computed as follows;

$$\text{VIF} = {}^{1}\!/_{1 - R^2 i} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (12)$$

where R^2 is for each auxiliary regression and i represents each of the independent variables.

According to Damodar and Porter (2004), any variable whose VIF exceeds ten should not be included in a regression. In this study, all the variables qualified to be included in the regression since, the VIF values were less than ten (see *Appendix 2*).

A Pearson correlation analysis was also done to ascertain if there was strong correlation between the independent variables. As shown in (*Appendix 3*) all the independent variables included in the analysis were not correlated.

3.8 Heteroscedasticity Test

Heteroscedasticity happens when the standard errors of a variable are non-constant. It does not cause bias in the coefficient estimates but it does make them less precise. Lower precision increases the likelihood that coefficient estimates are further from the correct population value.

Breusch-Pagan method was applied to test the presence of heteroscedasticity among the independent variables in the regression model (Wooldridge, 2015). Based on the results shown below, the null hypothesis was rejected and it was concluded that the variance of variable was constant across the error term in the second part of double-hurdle model.

For the first hurdle (probit regression)

chi2(1) = 98.66 at Prob > chi2 = 0.0000

For the second hurdle (truncated regression)

Ch2(1) = 0.06 at prob>chi (2) = 0.8015.

The first part of the double-hurdle (probit model) was significance and that is why there was robust standard error to take care of heteroskedasticity. The second part of double-hurdle (truncated model) was not significance since there was no heteroskedasticity in the model.

CHAPTER FOUR: RESULTS AND DISCUSSION

4.1 Descriptive Results

4.1.1 Farm and Farmer Characteristics

Table 3 presents the socio-economic characteristics and access to institutional support service of the surveyed households.

Table 3: Respondent's socio-economics and demographic characteristics

	Kajiado (n=164)			Makueni (n=234)			Pooled (n=398)		
Characteristics	**Adopters**	**Non-adopters**	**t-ratios**	**Adopters**	**Non-adopters**	**t-ratios**	**Adopters**	**Non-adopters**	**t-ratios**
Farmers characteristics									
Gender (%)	76(0.6)	43(0.5)	-0.257	77(0.5)	38(0.5)	-0.64	70(0.5)	47(0.49)	-0.367
Average age of respondents in years (mean)	44(7.4)	42(15.2)	-0.298	49(9.2)	44(15)	-2.039**	49(9.1)	43(15)	-2.575**
Marital status (% married)	100(0)	82(0.4)	-0.807	88(0.9)	84(0.4)	-0.746	89(0.3)	83(0.4)	-1.059
Primary education and above (% of respondents)	55(0.6)	57(0.5)	0.799	98(0.1)	91(0.3)	-1.707*	94(0.2)	74(0.4)	-3.202***
Average household size	6(1.2)	7(3.8)	0.694	6(1.3)	6(2.0)	0.161	6(1.3)	6(0.3)	1.633
Average number of meals per day	3(0)	2.9(0.2)	-0.259	2.9(0.3)	2.8(0.5)	-1.960*	2.9(0.3)	2.9(0.4)	-0.855
Average land size in acres	10.7(9.0)	17.6(26.2)	0.460	3.4(1.4)	7.01(11.3)	2.256**	3.8(2.7)	12(20.3)	2.912***
Institutional variables									
Access to extension services (% of respondents)	66.7(0.5)	46(0.5)	-0.709	76(0.5)	33(0.5)	-5.887***	74(0.4)	39(0.5)	-5.158***
Access to credit (% of respondents)	67(0.43)	33(0.5)	-1.225	20(0.4)	24.5(0.4)	0.657	23(0.4)	28(0.5)	0.872
Group membership (% of respondents)	100(0)	65.2(0.5)	-1.257	32(0.5)	74(0.4)	5.879***	36(0.5)	70(0.5)	4.980***
Access to information (% of respondents)	33(0.5)	36(0.5)	0.096	10(0.3)	43(0.5)	4.467***	11.3(0.3)	40(0.5)	4.084***

Note: Standard deviations are in parentheses

*****, **, *** denotes significant difference between adopters and non-adopters at 1%, 5% and 10%, respectively.

The findings revealed that all the surveyed individuals were aware of AI technology. However, not all of them actually used the technology on their herds. One-seventh of the pooled sample respondents adopted the AI technology. In Makueni County, one fifth of the respondents adopted AI, while, in Kajiado county, only 1.8% of the respondents are using the AI technology. This is an indication that, the agro-pastoralists in Makueni have somehow embraced the adoption of AI technology than the nomadic pastoralists in Kajiado County (Figure 6). The low adoption of AI technology is not unique to Kenyan ASALs; Lawrence et al. (2015) also found low adoption levels of 16% among dairy farmers in Kenya.

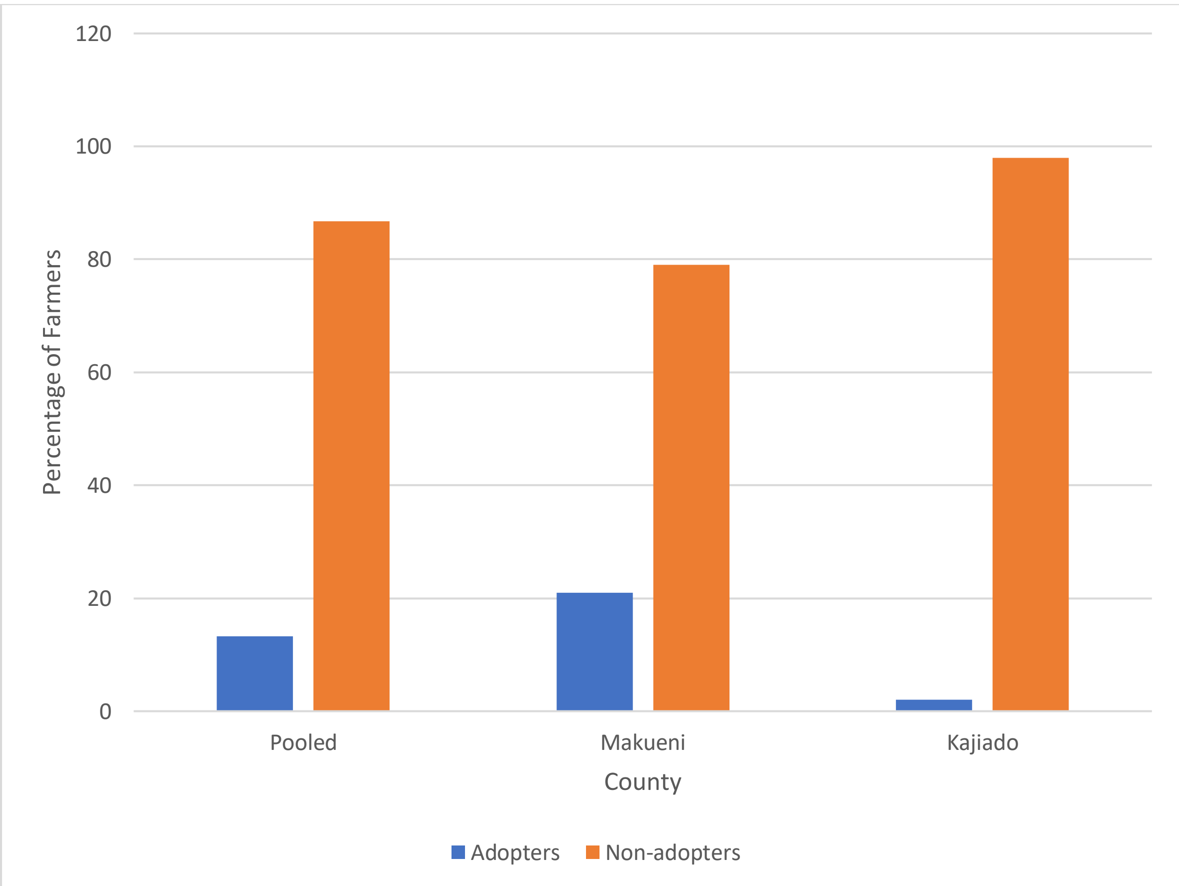

Figure 6: Adoption rates for artificial insemination in Makueni and Kajiado Counties

Source: Survey Data (2020).

From the pooled data, majority of the respondents were female (59.8%). This is because women in most cases stay at home making them accessible to the enumerators unlike men, who go out to social gatherings as well as attending to cattle in the grazing places.

The mean age of the respondents was 44 years with standard deviation of 15.7. Adopters were significantly older than the non-adopters. The livestock farmers in Makueni county were older than those in Kajiado county. Other studies also found that AI adopters were relatively older than non-adopters in Rwanda and Uganda (Mazimpaka et al., 2018; Kaaya et al., 2005).

All the adopters and four-fifth of non-adopters in Kajiado County were married. In Makueni county, slightly over four-fifth of both adopters and non-adopters were married. This could be because of the responsibilities associated with married people. This finding is similar to that of Namwata et al. (2010) who reported that, more than 68% of respondents were married.

The average family size of the respondents was six members. The non-adopters have larger household size than the adopters in Kajiado county while, the household size was the same for both adopters and non-adopters in Makueni county. The average land size for the households was approximately 10.6 acres. The average land size for livestock farmers in Kajiado is bigger than that in Makueni. This could be attributed to the fact that, farmers in Kajiado County are pastoralists who settled far apart while, those in Makueni are agro-pastoralists who settled close to each other due to limited land. In overall, adopters have smaller land size than their counterpart non-adopters.

The mean meals per day was 2.9 for the pooled sample. The essence of this variable was to know the level of poverty in the area of study. A farmer who hardly affords a meal per day may not be expected to adopt AI technology. Slightly over half of adopters and more than half of non-adopters in Kajiado County had completed primary school and above. In Makueni County, nearly all of adopters and non-adopters had primary school level and above. These findings are consistent with those of Wetengere (2009) who also reported high formal education among farmers in Tanzania. The distribution of level of education in Kajiado and Makueni counties is presented in Figure 7 below.

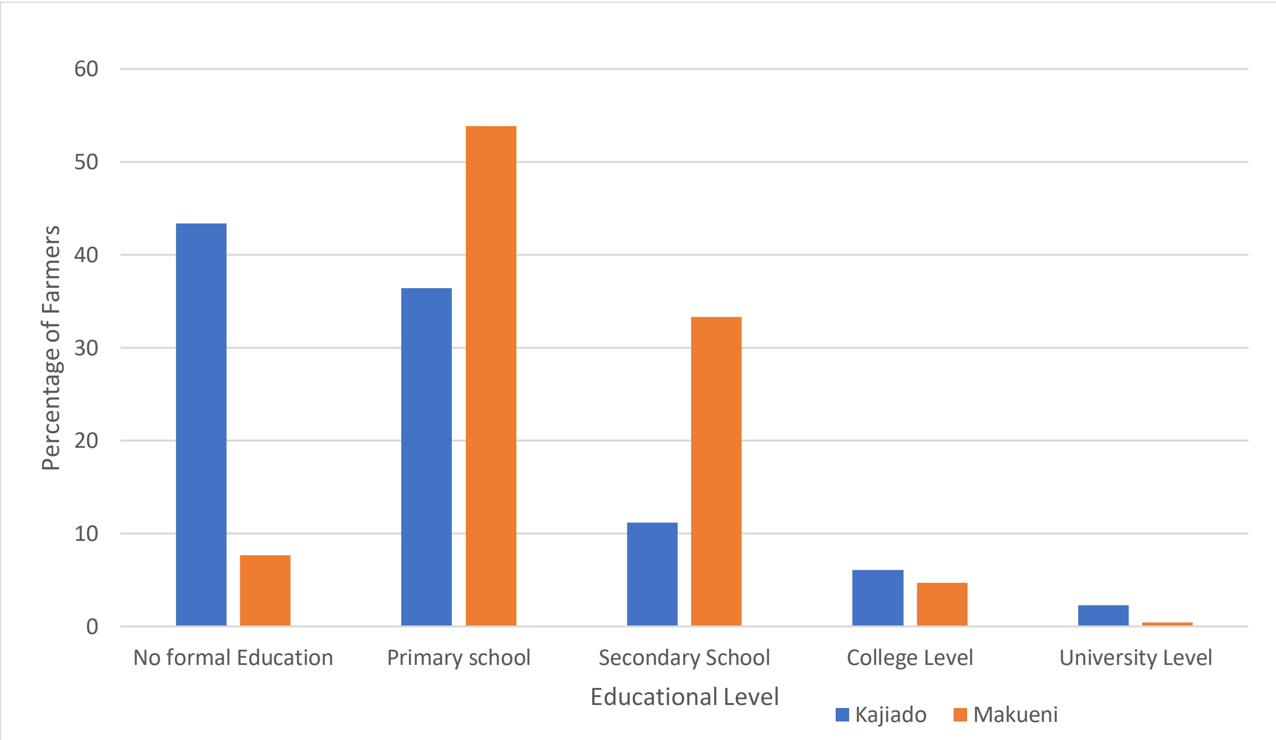

Figure 7: Distribution of education levels for respondents in Kajiado and Makueni Counties

Source: Survey Data (2020).

4.1.2 Access to Institutional Support Services

More than half of adopters and nearly half of the non-adopters in Kajiado County had access to extension services. In Makueni county, three-quarters and one-third of adopters and non-adopters respectively had access to extension services. In the pooled sample data, nearly three-quarter and slightly over one-third of adopters and non-adopters respectively had access to extension services in the last 12 months from either the government or private extension agents; the difference being statistically significant at 1%. This finding is consistent with Temba (2011) who revealed that majority of dairy farmers who had extension contact adopted new agricultural technologies.

Less than one-third of adopters and non-adopters in Makueni and for the pooled sample had applied for and received credit from either a bank, *Tetheka* or informal groups. Surprisingly, 67% of adopters and 33% of non-adopters in Kajiado whose AI adoption levels were almost negligible had accessed credit. This implies that the credit was not applied entirely in AI adoption.

More than half of the respondents were members of developmental groups such as women groups and livestock groups. In Kajiado county, all the adopters compared to more than half of non-adopters were members of developmental groups. In Makueni county, one-third of the adopters and about three-quarters of non-adopters were members of groups. Being a member of the informal developmental groups help farmers to learn and share experiences on new technologies such as AI.

From the overall data, slightly above one-third of the respondents had access to information on market prices, new technology and market needs from either government agents, neighbours, radio or newspapers. In Kajiado County, only one-third and slightly over one-third of adopters and non-adopters respectively had access to information. In Makueni County, one-eighth of adopters and less than half of the non-adopters had access to information. Having access to information is vital for livestock farmers to know the market price, new technology and the market needs that could possibly persuade them into adoption of the AI technology.

4.2 Determinants of Farmers' AI adoption Decisions and Intensity

Table 4 shows the factors that were hypothesized to influence farmer's decision to adopt AI and to what extent. These variables were analysed using double-hurdle model comprising of probit and truncated regression models.

Table 4: Double hurdle model results on factors influencing farmers' decision and intensity of AI adoption

	Probit regression (AI adoption, Yes = 1, 0 otherwise)				**Truncated regression (Dependent = proportion of calves bred from AI)**			
Variables	**Coefficient**	**std error**	**Z**	***p*<|Z|**	**Coefficient**	**std error**	**Z**	***p*<|Z|**
Access to extension services	0.823***	0.196	4.19	0.000	0.092	0.154	0.60	0.552
Age of household head	0.0155**	0.007	2.26	0.024	-0.007	0.008	-0.80	0.425
Gender of household head	-0.0603	0.209	-0.29	0.773	-0.119	0.117	-1.02	0.306
Education level of household head	0.909**	0.398	2.28	0.022	-0.964***	0.309	-3.12	0.002
Household size	-0.093**	0.039	-2.36	0.018	0.105**	0.053	1.99	0.046
Cattle farm size	0.682***	0.146	4.67	0.000	0.043	0.051	0.85	0.394
Access to information	-0.594**	0.263	-2.26	0.024	0.467**	0.234	2.00	0.046
Distance to nearby market	-0.120**	0.052	-2.32	0.020	-0.155**	0.066	-2.34	0.019
Herd size	-0.0456	0.030	-1.52	0.129				
Off-farm employment	-0.879***	0.242	-3.63	0.000				
Group membership	-0.560***	0.201	-2.79	0.005				
Access to credit	0.367	0.250	1.47	0.141				
Contract market	1.518*	0.820	1.85	0.064	0.218	0.457	0.48	0.633
Distance to nearby AI centre					0.166***	0.064	2.60	0.009
Risk associated with AI					0.224	0.480	0.47	0.642
AI cost					-0.0001	0.0001	-1.43	0.152
Dishonesty/mistrust					-0.528***	0.862	-2.93	0.003
Total household income					-0.196	0.180	-1.09	0.276
Sigma					0.377	0.038	10.04	0.000
Number of observations	398				53			
Wald chi2(14)	104.72				31.17			
Prob > chi2	0.000				0.0052			
Log pseudo likelihood	-90.366941				-23.04192			
Pseudo R2	0.4213							

***, **, * denotes significant difference between adopters and non-adopters at 1%, 5% and 10%, respectively.

4.2.1 Factors Influencing Decision to Adopt AI

Access to extension services was found to positively influence the adoption of AI technology. This means that, those who have access to extension services are more likely to adopt the AI than those without access to extension services. This is because extension agents act as a useful link between researchers and the farmers, hence reduce the transaction cost associated with technology adoption. This finding conforms with other studies such as Berhe et al. (2020) who found that, smallholder dairy farmers with regular contacts with extension agents helps them to access the vital information and skills about the new technology. The finding on the other hand is contrary to the observation of Oluoch-Kosura (2010) that access to extension services has negative effect in farmers' adoption decisions due to insufficient number of professional extension agents, which lead to irregular and poor-quality service to farmers.

Age of the household head was found to positively influence the adoption of AI technology. This is because older farmers have more experience. This finding is consistence with other studies that also found positive relationship between age and adoption of new technologies (Kaaya et al., 2005; Simon, 2006). However, this is contrary to Khainga et al. (2015) who found age to be negatively associated with adoption decision because younger farmers are less risk averse and are ready to invest in long term plan due to their age.

Education level of household head was found to have positive influence on the adoption. This is because farmers with formal education can easily comprehend and process information on new technologies such as AI. The finding is in line with other studies that also found that, smallholder dairy farmers who are relatively educated were more likely to adopt AI technology compared to their counterparts with lower education (Murage and Ilatsia, 2011; Ogola et al., 2015; Ingabire et al., 2018). The finding is however contrary to Samiee et al. (2009) who reported negative relationship between farmers' education and adoption decision of agricultural technology.

Household size was found to have negative effect on adoption of AI. The negative relationship implies that, the families with few members are more likely to adopt AI technology than those with more members. The results show that, an increase of household size by one member, leads to a decrease of chances of AI adoption by 9.3%. This could be attributed to the fact that, AI is not labour intensive as noted by other studies such as Semgalawe (1998), Kandoro (2008) and Tefera et al. (2014). But this finding contradicts that of Mignouna et al. (2011) which revealed positive effect of family size on adoption of agricultural technologies.

Contract market/farming was found to positively influence adoption of AI. The positive relationship implies that a farmer who involved in contract farming/market is more likely to adopt AI than the fellow farmer who is not involve in contract market. This could be attributed to the fact that the farmers who are involved in contract market are given training, assured market, veterinary services and information that help them to produce a quality product. Therefore, the null hypothesis is rejected and it is concluded that contract market had significance positive effect on the adoption of AI.

Off-farm employment of the household head was found to have negative effect on the adoption of AI. Perhaps, this could be explained by the possibility that such farmers invest their income in crop enterprises and other off-farm activities which are more beneficial and profiting to them than AI technology or it could be that, the off-farm engagements are too demanding to the point they could not find time to involve in other ventures. This is consistent with the observation by Berhe et al. (2020) that, pursuit of off-farm income reduced the labour that is supposed to be used in adopting the new technology by farmers. However, this is contrary to the argument by Reardon et al. (2007), Diiro (2013) and Tefera et al. (2014) that, off-farm employment help to overcome credit constraints faced by the rural households.

Group membership was found to negatively affect adoption of AI. Specifically, being a member of a developmental group decreases the chances of adopting AI by 56%. This can be attributed to the fact that, most of the decisions regarding livestock are made by men and these informal groups are largely female enterprises. This finding is consistent with Teferi et al. (2015) who found that farmers association/groups have negative effect on the adoption of agricultural technologies. On the contrary, Akin-Kara (2019) reported group membership to have a positive effect on AI adoption.

Distance to market was found to negatively affect the probability of farmers adopting AI. Specifically, an increase of distance to the nearest market by one kilometre decreases the probability of adopting AI technology by 12%. Market places are avenues where farmers share their experiences, lessons and information about their products, therefore, the shorter the distance, the ease to market access. This finding is in line with other studies such as Shiferaw and Tesfaye (2005) and Teferi et al. (2015).

Access to information on market price and new technologies was found to negatively affect adoption of AI. This implies that, those who have access to information have less probability to adopt AI. The negative relationship could be attributed to the unprofessionalism and irregular agents who provide poor-quality information. This finding conforms with Uaiene et al. (2009) findings who also reported the same. This is however, contrary to the observation by Bonabana-Wabbi (2002) that access to information reduces the uncertainty about a technology's performance and hence may change individual's assessment from purely subjective to objective over time.

Cattle farm size had positive effect on the adoption of AI technology. This could be attributed to the availability of space to accommodate more cattle in case of future expansion. This finding is consistent with Uaiene et al. (2009) and Mignouna et al. (2011) who reported a positive relationship between farm size and adoption of agricultural technology. However, this contradicts the observation by Yaron et al. (1992), Harper et al. (1990) and Njuguna et al. (2017) who reported opposite findings. Farmers with small land may adopt land-saving technologies such as zero grazing as an alternative to increase agricultural production.

4.2.2 Determinants of Intensity of AI Adoption

Distance to the AI centre was found to positively influence the extent of AI adoption. Specifically, a decrease of distance to nearby AI centre by 1 kilometre increase the chances of intensifying use of AI by 16.6%. This could perhaps be due to accessibility of services which, in turn reduce the transaction costs in term of searching for the service and information. The finding is in agreement with those of Murage and Ilatsia (2011) and Idrisa et al. (2012). On the other hand, the finding is contrary to that of Tefera et al. (2014) who found negative relationship between distance from AI station and intensity of AI adoption.

The dishonesty from the service providers was found to negatively influence the intensity of AI adoption. The negative relationship implies that, farmers who have experienced cases of cheating from the service providers are less likely to intensify the adoption of AI. Farmers have been complaining of cheating by the AI service providers, that is, the case where a farmer paid for insemination service to get the graded calves but later on during the calving period, the calf turns out to be of the zebu origin. This act discourages farmers from continuing with the use of AI service and they instead turn to bull service despite many advantages associated with AI technology. The variable was captured by asking a farmer whether he/she experience a case of paying for AI to get an improved breed but later on turns out to be of a zebu origin. The null hypothesis is therefore rejected and it is concluded that dishonesty from the service providers had a significant negative effect on the intensity of AI adoption.

Education level was found to have negative effect on the extent of AI adoption. This implies that, livestock farmers with less education are more likely to intensify the adoption of AI as compared to those with higher education. This could be attributed to the fact that, most highly educated people are engaged in off-farm employment activities which are too demanding hence, prevent them from engaging in the farming activities. The finding is in line with Mal et al. (2012) who reported negative association of education with intensity of adoption because educated farmers balanced land usage with other enterprises. They are risk averse through farm diversification. The findings contradict observations by Tefera et al. (2014), Bayan (2018) and Mahama et al. (2020) who noted that education level of head of household positively influence the extent of AI adoption.

The family size was found to have positive influence on the extent of AI adoption. Specifically, an increase of household size by one member increases the chances of intensifying AI adoption by 10.5%. This is because family size is simply used as a measure of labour availability. A larger household has the capacity to relax the labour constraints required to intensify the adoption of new technology. Other studies also reported the same results (Njuguna et al., 2017; Guye and Sori, 2020).

Access to information was found to have positive effect on the extent of AI adoption. This means that, livestock farmers who have access to information on market prices and technology benefits, are more likely to intensify the use of AI on their herds. Access to information is vital in that, it helps the farmers to make viable decisions in the absence of bounded rationality and also reduce the transaction cost of searching for information about the service. The findings are in line with other studies that also found that access to information positively impacts on the intensity of its adoption (Taye and Shanta, 2017; Mahama et al., 2020).

Distance to market was found to have negative influence on the extent of AI adoption. Specifically, an increase of distance to the nearest market by one kilometre decreases the probability of intensifying AI adoption by 15.5%. This is attributed to the fact that, market place is an important avenue where farmers share experiences, lessons and information regarding products. The finding conforms to the observations by Kunzekweguta et al. (2017), Njuguna et al. (2017), Bayan (2018) and Asfaw et al. (2019) who also reported negative relationship of distance to the nearest market with the intensity of AI adoption.

CHAPTER FIVE: SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Summary

The main purpose of this study was to assess the determinants of adoption of AI by the smallholder livestock farmers in the dryland production systems of Kenya. The study was conducted in Kajiado and Makueni Counties. Makueni county represents the agropastoral while, Kajiado represents the nomadic pastoralists production systems.

The specific objectives were to characterise the AI adoption rate among the smallholder livestock farmers in Kajiado and Makueni Counties, to analyse the factors influencing the adoption of AI by the smallholder livestock farmers and to assess the determinants of AI adoption intensity among the smallholder livestock farmers in the dryland areas. The STATA version 14 software was used to analyse the data. Descriptive statistics were used to characterize the adoption rate and demographic characteristics of households while; the double-hurdle model was applied to estimate the determinants of adoption and intensity of use of AI technology.

The results showed that, the overall adoption rate was 13.3% which is extremely low and appalling to the policy makers. The adoption rate was 21% and 1.8% in Makueni and Kajiado respectively. Slightly over three-quarters of the respondents had primary school and above. The mean age was 44 years with minimum age of 18 years and maximum age of 80 years. The mean household size and meal per day were 6 members and 2.9 meals, respectively. The mean total household land size own by AI adopters was 3.8 acres, while that of the non-adopters was 12 acres. Only slightly more than a quarter of respondents had access to credit, one-third had access to information on market prices and more than half were members of developmental groups, while less than half had access to extension services.

Results of the probit model showed that access to extension services, age of the household head, education of the household head, contract farming and livestock farm size had positive influence on AI adoption. On the other hand, family size, off-farm employment of the household head, access to information, group membership and distance to market had negative influence on farmers adoption decision.

The truncated regression results showed that distance to AI centre, household size and access to information on market prices had positive effect on intensity of AI adoption. On the contrary, dishonesty from the service provider, education level of household head and distance to market had negative effects on the intensity of adoption.

5.2 Conclusion

The livestock farmers in the study area were aware of AI technology. However, majority of them learnt of it from informal sources either from a friend, neighbour or from colleague; thus, the quality of information may not be adequate. Therefore, there is a need for the County government to focus more on the creation of formal awareness to allow farmers to understand AI better in terms of benefits associated with its use.

More female respondents participated in the survey compared to their male counterparts and more farmers in Makueni had education level of primary school and above than Kajiado, an indication that nomadic pastoralists have very low formal education.

The results revealed low access to institutional support services in the study area, particularly, access to extension services and information which are very vital in the adoption process. There is need to prioritize access to extension services and information for the livestock farmers to improve adoption of AI technology.

5.3 Recommendations

5.3.1 Policy Recommendations

The study recommends the respective County governments to invest in training and dissemination workshops to the livestock farmers on the practical application of AI, heat detection and other skills needed to operate the AI technology. The training could be coupled with farmers exchange visits to share experiences and learn from each other across production systems. This would give farmers necessary skills to operate the technology in the absence of extension agents and AI technicians. These trainings should also be directed to farmer groups to empower farmers' developmental groups and distribution of record keeping materials to promote AI adoption. The farmers' groups can be used as avenues of passing information regarding the importance of technologies. Hanging of posters of crossbreeds and calves bred with AI in their meetings places can encourage farmers to adopt the AI since seeing is believing.

The findings revealed the importance of access to extension services in the adoption process of AI. Therefore, to reduce the cost of logistics in disseminating information to the farmers, the study recommends the County governments of the two Counties to adopt application of ICT such as the use of mobile phone and radio to promote extension services. This will boost the existing extension service by increasing extension agent coverage at minimal cost and at the same time, farmers will be able to get information regarding AI at the comfort of their homes and farms. This can also enlighten farmers to know the importance of AI over the natural breeding. This would also separate the myths from the facts on farmers' perception toward AI technology and also for the livestock farmers to know that AI is not only meant for exotic breeds but also for indigenous breeds which seriously need genetic improvement.

The study recommends the need for service providers to expand AI centres to densely populated villages with high numbers of cattle for the ease of accessibility by the farmers. The oestrous period in a cow last for a short time and can be lost easily if the inseminator is located at distance. This could lead to repeated cases of insemination and the act may discourage farmers from intensifying the adoption of AI service. The government should put more focus on building road network to increase accessibility to the remotest villages which cannot be reached during wet seasons.

There is a need for the County governments of the two Counties to link the farmers with markets so that, they should have access to market for their products and information at ease. This could be done by supporting local existing markets for their products in their proximity to reduce transaction cost for looking for market. The respective County governments to source buyers for the commodities of their farmers to buy in their respective local existing markets.

Based on the results, there is low formal education level among farmers in Kajiado. In that regard, the study recommends the County government of Kajiado to come up with policy that encourage adult education among the pastoralists. For instance, embracing education for pastoralists initiative commonly known as mobile education and put more energy and resources in its implementation to achieve tangible results.

5.3.2 Limitations and Suggestions for Future Research

The limitation of the study's methodology was that, dishonesty from service providers variable was measured on the pretext that the farmer isolated the cow on heat to be served through AI to avoid contact with the bulls. However, if the isolation is not done properly considering the limited facilities, chances are, the bull and the cow on heat could mate in the field in absent of the owner and the calf could be from natural mating but not from AI service as perceived and therefore, the accusations labels on the service provider may not hold. Future research should look into the nature of isolation by the farmers to gauge the possibility of the cow on heat meeting with bull after AI service.

The study assumed that the two decisions (the decision to adopt or not to adopt and to what extent) were made independently/separately. However, this assumption might have weakness in that, some farmers might have made the two decisions jointly. Other studies may consider using the assumption that the farmers made the two decisions jointly to see if the results will have significant difference.

The study revealed low adoption of AI among the pastoralists in the ASALs. Therefore, further research can focus on the attitudes and perception of pastoralist communities toward AI as a breeding option. Future studies could also assess the effect of AI risk perception and community cultural aspects on its adoption.

REFERENCES

Abadi, T., Philip, D. and Moti, J. (2015). Factors that Affect the Adoption of Improved Maize Varieties by Smallholder Farmers in Central Oromia, Ethiopia. *Developing Country Studies, 5(15), 50-58.*

Akin-Kara (2019). Factors Affecting the Farmers' Decision on Artificial Insemination: A Case Study of Diyarbakir Province, Turkey. *Journal of Applied Ecology and Environmental Research, 17(1),1389-1399.*

Akudugu, M., Guo, E. and Dadzie, S. (2012). Adoption of Modern Agricultural Production Technologies by Farm Households in Ghana: What Factors Influence their Decisions? *Journal of Biology, Agriculture and Healthcare, 2(3), 1-13.*

Asfaw, A., Dessalegn, A. and Getachew, A. (2019). Adoption and Intensity of Adoption of Beekeeping Technology by Farmers: The Case of Sheko Woreda of Bench-Maji Zone, South West Ethiopia. *Ukrainian Journal of Ecology, 9(3),103-111.*

Atnafe, Y., Mugera, A., El-shater, T., Aw-hassan, A., Piggin, C., Haddad, A. and Loss, S. (2018). Technological Forecasting and Social Change Enhancing Adoption of Agricultural Technologies Requiring High Initial Investment Among Smallholders. *Technological Forecasting and Social Change*, 134(April), 199-206. https://doi.org/10.1016/j.techfore.2018.06.006.

Baltenweck, I., Ouma, R., Anunda, F., Mwai, O. and Romney, D. (2004). Artificial or Natural Insemination: The Demand for Breeding Services by Smallholders. Paper presented at the 9th KARI Biennial Scientific Conference/Kenya Agricultural Research Forum, 8-12 November 2004, Nairobi, Kenya.

Bayan, B. (2018). Factors Influencing Extent of Adoption of Artificial Insemination (AI) Technology among Cattle Farmers in Assam. *Indian Journal of Economics and Development, 14(3), 528-534.*

Berhe, A., Muluken, G. and Jemal, Y. (2020). Adoption of Artificial Insemination Service for Cattle Crossbreeding by Smallholder Farmers in Laelay-Maichew District. Tigray, Ethiopia. *Journal of Development and Agricultural Economics, 12(2), 104-112.*

Bonabana-Wabbi, J. (2002). Assessing Factors Affecting Adoption of Agricultural Technologies: The Case of Integrated Pest Management (IPM) in Kumi District, M.Sc. Thesis, Virginia Polytechnic Institute of State University.

CIDP (2018-2022a). Makueni County Integrated Development Plan for 2018-2022.

CIDP (2018-2022b). Kajiado County Integrated Development Plan for 2018-2022.

Cochran, W. (1963). Sampling Techniques, 2nd Edition. New York: John Wiley and Sons, Inc.

Cragg, J. (1971). Some Statistical Models for Limited Dependent Variables with Application to the Demand for Durable Goods. *Econometrics, 39 (5), 829-844.*

Damodar, G. and Porter, D. (2004). Basic Econometrics (Fourth edition). Editura McGraw-Hill.

Diiro, G. (2013). Impact of Off-farm Income on Technology Adoption Intensity and Productivity: Evidence from Rural Maize Farmers in Uganda. International Food Policy Research Institute, Working Paper 11.

Doss, C. (2003). Understanding Farm Level Technology Adoption: Lessons Learned from CIMMYT's Micro Surveys in Eastern Africa. CIMMYT Economics Working Paper 03-07. Mexico, D.F.: CIMMYT.

EADD (2011). Constraints to Use of Artificial Insemination Service and possible Solutions. East Africa Dairy Development Project Baseline Survey report 2011.

Elliott, B., Parcell, J. and Palterson, D. (2013). Factors Influencing Beef Reproductive Technology Adoption. *Journal of the American Society of Farm Managers and Rural Appraisers (ASFMRA), (2013), 100-119.*

ERA (2015). Economic Review of Agriculture, Ministry of Agriculture, Livestock and Fisheries, 2015.

FAO (2019). Dairy Market Review. March, 2019.

Feder, G., Just, R. and Zilberman, D. (1985). Adoption of Agricultural Innovations in Developing Countries: A Survey." *Economic Development and Cultural Change, 33(2), 255-298.*

Fernandez-Cornejo, J., Mishra, A., Nehring, R., Hendricks, C., Southern, M., and Gregory, A. (2007). Off-Farm Income, Technology Adoption, and Farm Economic Performance, Agricultural Economics Report No. 36. Washington, *DC:* USDA ERS.

Gebregziabher, G. and Holden, S. (2011). Does Irrigation Enhance and Food Deficits Discourage Fertilizer Adoption in A Risky Environment? Evidence from Tigray, Ethiopia. *Journal of Development and Agricultural Economics, 3(10), 514-528.*

Gebremedhin, B. and Swinton, S. (2003). Investment in Soil Conservation in Northern Ethiopia: The Role of Land Tenure Security and Public Programs. *Journal of Agricultural Economics, 29(1), 69–84.*

Ghimire, R., Wen, C. and Shrestha, R. (2015). Factors affecting Adoption of Improved Rice Varieties Among Rural Households in Central Nepal. *ScienceDirect- Rice Science, 22(1), 35-42.*

Gillespie, J., Nehring, R. and Sitienei, I. (2014). The Adoption of Technologies, Management Practices and Production Systems in U.S Milk Production. *Agricultural and Food Economics, 2(17) 1-24 http://www.agrifoodecon.com/content/2/17*

Greene, W. (2007). Econometric Analysis. 6th Edition. Macmillan, New York, USA.

Greene, W. (2008). Econometric Analysis, 6th Edition. Prentice-Hall, Upper Saddle River, NJ.

Guye, A. and Sori, O. (2020). Factors Affecting Adoption and its Intensity of Malt Barley Technology Package in Malga Woreda Southern Ethiopia. *Journal of Agricultural Economics and Rural Development, 6(1), 697-704.*

Hall, B. and Khan, B. (2002). Adoption of New Technology. New Economy Handbook.

Harper, J., Rister, M., Mjelde, J., Drees, M. and Way, M. (1990). Factors Influencing the Adoption of Insect Management Technology." *American Journal of Agricultural Economics, 72(4), 997-1005.*

Horppila, J. and Peltonen, H. (1992). Optimizing Sampling from Trawl Catches: Contemporaneous Multistage Sampling for Age and Length Structures. *Canadian Journal of Fisheries and Aquatic Science, 49(8), 1555-1559.*

Howley, P., Donoghue, C. and Heanue, K. (2012). Factors Affecting Farmers Adoption of Agricultural Innovations: A panel Data Analysis of the Use of Artificial Insemination among Dairy Farmers in Ireland. *Journal of Agricultural Science, 4(6), 171-179 http://dx.doi.org/10.5539/jas.v4n6p171.*

Idrisa, Y., Ogunbameru, B. and Madukwe, M. (2012). Logit and Tobit Analyses of the Determinants of the Likelihood of Adoption and Extent of Adoption of Improved Soybean seed in Borno State, Nigeria. *Greener Journal of Agricultural Sciences, 2(2), 037- 045.*

Ingabire, M., Yonggong, L., Chrisostom, J. and Alhassan, H. (2018). Factors Affecting Adoption of Artificial Insemination Technology by Small Dairy Farmers in Rwanda: A Case of Rwamagana District. *Journal of Economics and Sustainable Development, 9(12), 1-8. ISSN 2222-1700 (Paper) ISSN 2222-2855 (Online)*

Intergovernmental Panel on Climate Change, IPCC (2014). Climate Change 2014–Impacts, Adaptation and Vulnerability: Regional Aspects. Cambridge University Press.

Jones, A. (1989). A Double-hurdle Model of Cigarette Consumption. *Journal of Applied Econometrics, 4(1), 23-39.*

Kaaya, H., Bashasha, B. and Mutetikka, D. (2005). Determinants of Utilization of AI Services Among Ugandan Dairy Farmers. Department of Veterinary Services and Animal Industry. Makerere University, Kampala, Uganda. pp. 34 - 43.

Kandoro, B. (2008). Assessment of Factors Affecting Adoption of Animal Traction Technology: A Case Study of Muheza District. Sokoine University of Agriculture. Morogoro, Tanzania. 98pp.

Kebebe, G., Oosting, J., Baltenweck, I. and Duncan, J. (2017). Characterisation of Adopters and Non-Adopters of Dairy Technologies in Ethiopia and Kenya. *Tropical Animal Health and Production,* 51, 395-409. DOI 10.1007/s11250-017-1241-8.

Keelan, C., Thorne F., Flanagan P. and Newman C. (2009). Predicted Willingness of Irish Farmers to Adopt GM Technology. *The journal of AgBioForum,12(3 and 4), 394-403.*

Kenya Institute of Public Policy and Research analysis (KIPPRA). (2018). Kenya Economic Report 2018.

Kenya National Bureau of Statistics (KNBS) (2017a). County Statistical Abstract, Kajiado County.

Kenya National Bureau of Statistics (KNBS) (2017b). County Statistical Abstract, Makueni County.

Kenya National Bureau of Statistics (KNBS) (2018a). Kenya Economics survey.

Kenya National Bureau of Statistics (KNBS) (2018b). The 2015/16 Kenya Integrated Household Budget Survey (KIHBS) Reports.

Kenya National Bureau of Statistics (KNBS) (2019). Economic Survey 2019.

Khainga D., Obare, G. and Murage A. (2015). Ex-ante Perceptions and Knowledge of Artificial Insemination among Pastoralists in Kenya. *Livestock Research for Rural Development, 27 (4), 1-11*.

Khainga, D., Obare, G. and Nyangeno, J. (2018). Estimating Pastoralists Willingness to Pay for Artificial Insemination in Arid and Semi-Arid Lands of Kenya. *Journal of Development and Agricultural Economics*, *10 (8), 261-270.*

Khanal, A. and Gillespie, J. (2011). Adoption and Profitability of Breeding Technologies on United States Dairy Farms, Southern Agricultural Economics Association Annual Meeting, Corpus Christi, TX, February 5-8.

Kunzekweguta, M., Rich, K. and Lyne, M. (2017). Factors Affecting Adoption and Intensity of Conservation Agriculture Techniques Applied by Smallholders in Masvingo District, Zimbabwe. *Journal of AGREKON, 56(4) 330-336.*

Kuti, W. (2015). Determinants of Adoption of Improved Maize Varieties in Osun State, Nigeria. *International Journal of Agricultural Economics and Extension, 3 (2), 115-121.*

Kwach, J. (2018). Beef Farming in Kenya in 2019. Is it worth it? *Published by Tuko newspaper, Kenya.*

Lavison, R. (2013). Factors Influencing the Adoption of Organic Fertilizers in Vegetable Production in Accra, M.Sc. Thesis, University of Ghana, Ghana.

Lawrence, F., Mutemboi, H., Lagat, J., Mburu, J., Amimo, J. and Okeyo, A. (2015). Constraints to Use of Breeding Services in Kenya.

Little, P. and McPeak, J. (2014). Resilience and Pastoralism in Africa South of the Sahara, with A particular focus on the Horn of Africa and the Sahel, West Africa. 2020 Conference Paper 9, May 2014.

Loevinsohn, M., Sumberg, J. and Diagne, A. (2013). Under What Circumstances and Conditions Does Adoption of Technology Result in Increased Agricultural Productivity? Protocol. London: EPPI Centre, Social Science Research Unit, Institute of Education, University of London.

Magotsi, D.L. and Adan, F.A. (2019). Fostering Peace, Security and Socio-economic Development of the Pastoralist Counties. Pastoralists Leadership Summit Conference, Garissa, 28Th February to 3rd March 2019.

Mahama, A., Awuni, A., Mabe, N. and Azumah, B. (2020). Modelling Adoption Intensity of Improved Soybean Production Technologies in Ghana. Generalised Poisson Approach. *Helivon Journal*, https: doi.org/10.1016/j.heliyon. 2020.e03543.

Maina, W. (2018). "The World Largest Exporter of Beef" WorldAtlas. December, 10, 2018. worldatlas.com/articles/the-world-s-largest-exporters-of-beef.html.

Makokha, S. (2006). Analysis of Factors Influencing the Adoption of Dairy Technologies in Western Kenya. PhD Thesis, University of Nairobi.

Mal, P., Anik, A., Bauer, S. and Schmitz, P. (2012). Bt Cotton Adoption: A Double-hurdle Approach for North Indian Farmers. *AgBioForum, 15(3), 295-302.*

Mazimpaka, E., Bukenya, M., Edmund, M. and Bunza, F. (2018). Factors That Limit Delivery and Adoption of Artificial Insemination in Rwanda: Case Study in Rukomo Sector of Nyagatare District, Rwanda. *American Journal of Agricultural Science, 5(2) 28-34.*

Mercer, E. and Pattanayak, S. (2003). Agroforestry Adoption by Smallholders. In Forests in a Market Economy. Dordrecht Kluwer Academic Publishers. *Forestry Sciences Series, 72(1), 283-299.*

Mignouna, D., Manyong V., Rusike, J., Mutabazi, S., and Senkondo, M. (2011). Determinants of Adopting Imazapyr-Resistant Maize Technology and its Impact on Household Income in Western Kenya: *AgBioforum, 14(3), 158-163.*

Minhat, H. (2015). An Overview on The Methods of Interviews in Qualitative Research. *International Journal of Public Health and Clinical Sciences,* 2(1), 2289-7577.

Ministry of Agriculture (MoA) (2017). Kenya's Dairy Nationally Appropriate Mitigation Action (NAMA). Concept Note. A Proposal for Green Climate Fund Project. January 2017.

Ministry of Agriculture, Livestock, Fisheries and Irrigation (MoALF) (2019). State Department for Livestock. Draft National Livestock Policy, Kenya. February, 2019.

Ministry of Agriculture, Livestock, Fisheries and Cooperatives and Kenya Leather Development Council (MoALF, 2020). The Kenya National Leather Development Policy Draft. August, 2020.

Moffat, P. (2005). Hurdle Model of Loan Default: *Journal of the Operational Research Society, 56(9), 1063-1071.*

Mujeyi, K. (2009). Socio-Economics of Commercial Utilization of Jatropha (Jatroph Curcas) in Mutoko District, Zimbabwe. *Journal of Sustainable Development in Africa, 11 (2), 36-53.*

Murage, A. and Ilatsia, E. (2011). Factors That Determine Use of Breeding Services by Smallholder Dairy Farmers in Central Kenya. *Tropical Animal Health and Production, 43(1), 199–207.*

Muriuki, H. (2012). Dairy Development, Food and Agriculture Organization (FAO), Rome Italy, 2012.

Mutembei, H., Tsuma, V., Muasa, B., Mraya, J. and Mutiga, E. (2015). Bovine Invitro Embryo Production and its Contribution Towards Improved Food Security in Kenya. *African Journal of Food, Agriculture, Nutrition and Development, 15(1), 9722-9743.*

Mwangi, M., and Kariuki, S. (2015). Factors Determining Adoption of New Agricultural Technologies by Smallholder Farmers in Developing Countries. *Journal of Economics and Sustainable Development, 6(5), 208-217.*

Namwata, B., Lwelamira, J. and Mzirai, O. (2010). Adoption of Improved Agricultural Technologies for Irish Potatoes (Solanum Tuberosum) Among Farmers in Mbeya Rural District, Tanzania: A Case of Ilungu Ward. *Journal of Animal and Plant Sciences, 8(1), 927 - 935.*

National Drought Management Authority (NDMA) (2016). Drought early warning bulletin for West Pokot County for April 2016.

Njuguna, C., Kabuage L. and Bett E. (2017). Determinants of Adoption and Intensity of Use of Brooding Technology in Kenya: The Case of Indigenous Chicken Farmers in Makueni and Kakamega Counties, Kenya. *African Journal of Agricultural Economics and Rural Development,5 (2), 532-538.*

Nyariki, D. (2017). Assessment of The Economic Valuation of Pastoralism in Kenya. A Report for IGAD, Nairobi, Kenya.

Obisesan, A. (2014). Gender Differences in Technology Adoption and Welfare Impact Among Nigerian Farming Households, MPRA Paper No. 58920.

Odero-Waitituh, J. (2017). Smallholder Dairy Production in Kenya; A Review. *Livestock Research for Rural Development, 29(7), 1-10.*

Ogola, T., Lagat, J. and Kosgey, I. (2015). Factors Influencing Smallholder Dairy Farmers Participation in Voluntary Compliance of Decent Work Practices: Case Study in Nakuru County Kenya. *International Journal of Humanities and Social Sciences,* 5(3), *2221-0989 (Online).*

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

Ongoche, I., Otieno, D. and Oluoch-Kosura, W. (2017). Assessment of Factors Influencing Smallholder Farmers' Adoption of Mushroom for Livelihood Diversification in Western Kenya. *African Journal of Agricultural Research, 12(30), 2461-2467*. https://doi.org/10.5897/AJAR2017.12397.

Otieno, D. (2013). Market and Non-Market Factors Influencing Farmers Adoption of Improved Beef Cattle in Arid and Semi-Arid Areas of Kenya. *Journal of Agricultural Science, 5(1), 32-43.*

Pierpaoli, E., Carli, G., Pignatti, E. and Canavari, M. (2013). Drivers of Precision Agricultural Technologies Adoption: A Literature Review. *Procedia technology. 8(2013), 61-69.*

Rahm, R. and Huffman, W. (1984). The Adoption of Reduced Tillage. The Role of Human Capital and Other Variables. *American Journal of Agricultural Economics, 66(4), 405-413.*

Reardon, T., Stamoulis, K. and Pingali, P. (2007). Rural Nonfarm Employment in Developing Countries in an era of Globalization." *Agricultural Economics, 37(s1),173–183.*

Rogers, E. (2003). Diffusion of innovations (5th ed.). New York: Free Press.

Sadoulet, E. and de Janvry, A. (1995). Quantitative Development Policy Analysis. Baltimore: John Hopkins University Press.

Samiee, A., Rezvanfar A. and Faham, E. (2009). Factors Affecting Adoption of Integrated Pest Management by Wheat Growers in Varamin County, Iran. *African Journal of Agricultural Research, 4(5), 491-497.*

Semgalawe, Z. (1998). Household Adoption Behaviour and Agricultural Sustainability in The North- Eastern Mountains of Tanzania. The Case of Conservation in The North Pare and West Usambara Mountains. PhD Thesis, Wageningen Agricultural University, The Netherlands. 137pp.

Shiferaw, F. and Tesfaye, Z. (2005). Adoption of Improved Maize Varieties in Southern Ethiopia: Factors and Strategy Options. *Food Policy, 31(5),442–457*.

Shiferaw, B., Kebede, T. and You, L. (2008). Technology Adoption Under Seed Access Constraints and the Economic Impacts of Improved Pigeon pea Varieties in Tanzania. *Agricultural Economics, 39(3), 309-323.*

Simon, S. (2006). Adoption of Rotational Woodland Technology in Semi-Arid Areas of Tanzania: The Case of Tabora Region. Sokoine University of Agriculture. Morogoro, Tanzania, 237pp.

Taye, H. and Shanta, K. (2017). Factors Affecting Small Dairy Farmers' Adoption and Intensity of Adoption of Artificial Insemination Technology: A Case Study of Southern Ethiopia. *International Journal of Agricultural Science and Research (IJASR), 7 (6),335-346.*

Tefera, S, Job, L. and Hillary, B. (2014). Determinants of Artificial Insemination Use by Smallholder Dairy Farmers in Lemu-Bilbilo District, Ethiopia. *International Journal of African and Asian Studies, 4(2014), 91-98.*

Teferi, A., Damas, P., and Moti J. (2015). Factors That Affect the Adoption of Improved Maize Varieties by Smallholder Farmers in Central Oromia, Ethiopia. *Developing Country Studies, 5(15), 50-59. ISSN 2225-0565 (Online)*

Tegegne, Y. (2017). Factors Affecting Adoption of Legume Technologies and Its Impact on Income of Farmers: The Case of Sinana and Ginir Woredas of Bale Zone. MSc Thesis, Haramaya University, Ethiopia.

Teklewold, H., Dadi, L., Yami, A., and Dana, N. (2006). Determinants of Adoption of Poultry Technology: A Double-Hurdle Approach. *Livestock Research for Rural Development, 18(3), 40-49.*

Temba A. (2011). Factors Affecting Adoption of Artificial Insemination Technology by Dairy Farmers in Kinondoni District. MSc Thesis, Sokoine University of Agriculture. Morogoro, Tanzania.

Tey, Y., Li, E., Bruwer, J. and Mahir, A. (2017). Factors Influencing the Adoption of Sustainable Agricultural Practices in Developing Countries. *Environmental Engineering and Management Journal*, 16(2), 337-349.

Thornton, P., Steeg, J., Notenbaert, A. and Herrero, M. (2008). The livestock-climate-poverty nexus: A discussion paper on ILRI research in relation to climate change.

Uaiene, R., Arndt, C., and Masters, W. (2009). Determinants of Agricultural Technology Adoption in Mozambique. Discussion papers No. 67E.

United Nation (UN). (2019). The Sustainable Development Goals Report 2019. United Nations New York, 2019.

UNPD (United Nations Population Division). (2008). The 2006 Revision and World Urbanization Prospects: the 2005 Revision. Population Division of the Department of Economic and Social Affairs of the United Nations Secretariat, World Population Prospects. See http://esa.un.org/unpp.

USDA, (2019). Brazil Once Again Becomes the World's Largest Beef Exporter.

USDA, (2020). Livestock and Poultry: World Markets and Trade.

Vacquie, L., Houet, T., Sohl, T., Reker, R. and Sayler, K. (2015). Modelling Regional Land Change Scenarios to Assess Land Abandonment and Reforestation Dynamics in the Pyrenees. Paris, France. *Journal of Marine Technology Society, 12(4), 905-920.*

Wakhungu, J., Wesongah, G., Tura G., Msalya, D., Grace, F., Unger, F. and Alonso S. (2014). Pastoralism in Kenya and Tanzania: Challenges and Opportunities in Animal Health and Food Security. In Poster Prepared for the 6th All Africa Conference on Animal Agriculture. Nairobi: ILRI Www.Slideshare.Net/ILRI/ Pastoralism-Kenya-Tanzania.

Walton, J., Lambert, D., Roberts, R., Larson, J., English, B. and Larkin, S. (2010). Adoption and Abandonment of Precision Soil Sampling in Cotton Production. Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Orlando, FL, July 27-29, 2008.

Wetengere, K. (2009). Socio-Economic Factors Critical for Adoption of Fish Farming Technology: The Case of Selected Villages in Eastern Tanzania. *International Journal of Fisheries and Aquaculture, 1 (3), 28 – 37.*

Wooldridge, J. (2015). Introductory Econometric. A Modern Approach, Fifth edition. Nelson Education.

Yaron, D., Dinar A. and Voet, H. (1992). Innovations on Family Farms: The Nazareth Region in Israel. *American Journal of Agricultural Economics,* 74(2)*, 361-370.*

APPENDICES

Appendix 1: Household Survey Questionnaire

STUDY QUESTIONNAIRE

In this survey, only households that have indigenous cattle are eligible for interview. Only one person should be interviewed in the selected household. The interviewee, referred to here as “respondent” must be an individual who normally makes farm decisions in the household. In case the main decision maker is not available, his/her deputy should be interviewed.

Objective of the Survey (the enumerator should explain this part to the respondent)

The purpose of this survey is to obtain information on various aspects indigenous cattle production and adoption rate of artificial insemination on their head. Information obtained is strictly for academic and research purposes only and responses obtained will be treated with confidentiality. This interview is voluntary and will take approximately 1 hour. Your participation will be highly appreciated. I would like to request your permission to begin the survey now.

County………………………………**Subcounty**…………………………**Village**…………

Date………………………

Questionnaire number……...

Name of Enumerator……………………………………………

Please tick the appropriate box

Section A: Cattle Production

1 What type of cattle do you owned?

Breeds	Number	Duration
Zebu		
Boran		
Sahiwal		
Crosses		
Hampires		
Other……………..Specify		

2 How many years have you kept this type of cattle?

3 What acres of land do you used to keep your cattle?

4 Have you ever lost your cattle through one of the following? Tick all that apply

Cause of loss	Did cattle die from this cause? (Tick where applicable)		If yes, please indicate the number of cattle lost
	Yes	No	
Disease			
Drought			
Disputes over pastures and water			
Attack by wild animals			
Other factors(specify)			

Section B: Production services

5 Have you ever heard of artificial insemination (AI)?

A: Yes ☐ B: No ☐

6 Where did you hear it from?

Source of information	Tick one option
Neighbour	
Radio	
Extension agent	
Politicians	
Other...specify	

7 Have you used AI on your herd for the last 12 months? If yes go to 9

A: Yes ☐ B: No ☐

8 Why if No?

Reasons	Tick only one option
Expensive	
Complicated	
Not important	
Other…. specify	

9 Who provided it if yes?

A: Government ☐ B: Private ☐

10 Have you ever experienced any difficulties in using AI?

A: Yes ☐ B: No ☐

11 Please tick the challenges from the table below

Challenges	Tick one option
Too Expensive	
Too far from inseminator	
Too many repeats	
Other………. specify	

12 Is there a case where your cow was inseminated but failed?

A: Yes B: No

13 How far is AI centre from your home? Give your respond in Km

14 Do you get any technical assistance on how to use AI?

A: Yes ☐ B: No ☐

15 How about from the following

Source	Tick one option
Government extension agent	
Private provider	
Neighbour	
Other……. specify	

16 How many cows/calves were born using AI on your herd?

17 Do you fear using AI?

A: Yes ☐ B: No ☐

18 What is your greatest fear in using AI?

Fear	Tick all that apply
Failed insemination	
Expensive	
Dishonesty from the provider	
Other……Specify	

19 How much do you pay for AI service? Please indicate your respond in Ksh

20 Have you ever experienced any case you paid for AI to get exotic breed and then it turns out that it was actually Zebu?

A: Yes ☐ B: No ☐

21 who did that to you?

A: Government inseminator ☐ B: Private inseminator ☐

22 Did you consider quitting using AI after the incidence?

A: Yes B: No

23 Based on your experience, is AI beneficial to you?

A: Yes ☐ B: No ☐

24 Between AI and Natural service, which one do you prefer?

A: AI ☐ B: Natural ☐

25 Is AI against your culture or belief or what is your perception toward it?

A: Yes ☐ B: No ☐

26 Did you receive any veterinary service for the last 12 months?

A: Yes B: No

27 where do you get veterinary service from?

Source	Tick all that apply
Government officer	
Private provider e.g. Ngo, private company or individual	
Neighbour	
Other…….Specify	

28 Where do you get the feed for your cattle?

Feed	Average quantity used per cattle per month	Total cost in Ksh per month
a) Purchased feed		
Silage e.g. sunflower, corn (Kilograms)		
Fodder e.g. hay, maize stalk/Stover, wheat straw, sugarcane straw, rice straw, grass (Kilogram)		
Other feeds e.g. soybean urea (kilogram)		
b) feeds produced and feed on the farm		
Silage e.g. sunflower, corn (kilogram)		
Fodder e.g. hay, maize stalk/Stover, wheat straw, sugarcane straw, rice straw, grass (kilogram)		
Other feeds e.g. soybean, urea (kilogram)		

c)Natural pasture		

Section C: Household Asset

29 How many acres of land do your household own?

30 Do your household have any other enterprise apart from livestock keeping

A: Yes B: No

31 Which one?

Enterprise	Tick all that apply
Maize farm	
Pig farm	
Shop	
Poultry	
Other……..Specify	

32 Please provide the information on cattle entitlement

	Calves	**Heifers**	**cows**	**Bull**
How many do you have?				
How many did you buy?				
What was the average price?				
How many did you receive from other source? E.g. dowry or gifts				
How many did you use for other purpose? E.g. dowry or gifts				
How many did you sell and used the money for other family expenses?				

Section D: Institution support services

33 Did you get the livestock extension service for the last 12 months?

A: Yes ☐ B: No ☐

34 Who was the main provider for the livestock extension service for the last 12 months?

Provider	Tick one option
Government Officer	
Private provider e.g. Ngo, private company or individual	
Other…..Specify	

35 How often does the main livestock extension service provider visit?

Frequency	Tick one option
Weekly	
Every two weeks	
Every three weeks	
Once a month	

36 Do they trains you on animal husbandry when they come?

A: Yes ☐ B: No ☐

37 Which of the following do you normally sell your cattle to?

Channel	Tick all that apply
Open market centre	
Slaughter house/butcheries	
Kenya meat commission (KMC)	
Private exporters e.g. global livestock traders' company or middlemen	
Others e.g. neighbours or breeders or specify	

38 What is the approximate distance of market from your home to where you sell your cattle? (Km)

39 Do you normally sell the cattle through prior agreement (contract agreement)

A: Yes B: No

40 Does the contract agreement include the following?

Price	Yes/No
Transportation/delivery	Yes/No
Others…. specify	

41 Do you normally receive market information for cattle (price of cattle) before taking your cattle to the market?

A: Yes B: No

42 How frequent do you receive market information?

Frequency	Tick one option
Daily	
weekly	
Every two weeks	
Every three weeks	
Once a month	

43 How do you get market information about the prices

Source of information	Tick all that apply	Arrange them in order of importance
Mobile phone		
Workshop/group meeting		
Television		
Radio		
Internet		
Newspaper		
Advertisement on noticeboard		
Friends/neighbours		
Government staff e.g. extension agents or politicians		

44 Have you ever applied for credit for last 12 months? If no, go to number 48

A: Yes ☐ B: No ☐

45 From which source if yes?

Source of credit	**Amount applied**	**Amount paid**	**Amount repaid**	**Amount not repaid**
Tetheka Fund				
Uwezo Fund				
KREP (Financial service association)				
Kenya Women Finance				
Equity Bank				
Agricultural finance Cooperative (AFC)				
Family/Neighbour				
Other…………Specify				

46 How did you use the credit you took?

Activities	Percentage used
AI service	
Family survival	
Crop enterprise	
Poultry enterprise	

47 Have you started the pay back process for the credit?

A: Yes ☐ B: No ☐

48 Why if not applied?

Reasons for not applying for credit	Tick one option
There is no credit service around here	
Their interest rate is high	
They need collateral for loan	

49 Are you a member of any development group?

A: Yes ☐ B: No ☐

50 Which one?

Groups	Tick all that apply	How long
Women group		
Livestock group		
Men group		
Water user committee		

52 Do you pay membership subscription fee?

A: Yes ☐ B: No ☐

53 How regular do you attend the meeting?

Frequency	Tick one option
Daily	
Weekly	
Every two weeks	
Every three weeks	
Once a month	

54 Do you participate in decision making in your group?

A: Yes ☐ B: No ☐

Section E: Off-farm activities

55 Do you have another job apart from keeping cattle?

A: Yes ☐ B: No ☐

56 Where do you work?

Government	Approximated amount per month (Ksh)
Private	
Own business	
Government	
Other……..Specify	

57 Do you invest the income you get from the off-farm?

A: Yes ☐ B: No ☐

58 What did you invest them into?

Utility	Tick all that apply
Family Use	
Hospital bill	
School fees	
Buy more cow	
Start a business	
Other……. Specify	

Section F: Household Characteristics

59 Sex of respondent

A: Male☐ B: Female ☐

60 Position of respondent in the household. Tick one option

Head of household	
Spouse	
Son	
Daughter	
Relative e.g. Uncle, aunt,	

61 Age of respondent

62 Marital status

Status	Tick one option
Single	
Married	
Divorced	
Widow	

63 Your level of education

Level	Tick
No formal education	
Primary school level	
Secondary school level	
College level	
University level	

64 How many are you in your household?

Total number	
Adult	
Children	
Male	
Female	

65 What is the total income of the family per month?

Income in Shillings	Tick one option
0-10,000 Sh	
11000-15,000 Sh	
16000-20,000 Sh	
30,000 Sh and above	

66 How many meals do you have per day?

Number of meals	Tick only one option
One per day	
Two per day	
Three per day	

67 How many times on average per month do you missed meal?

Missed number of meals per month	Tick one option
1-2 times	
3-6 times	
7 times	

68 Is there any case where one of the family members was sent to the relative in town or other place because there was no food?

A: Yes B: No

69 Have you ever received any training in the following? Tick all that apply

Training	Tick all that apply
Livestock breeding	
Veterinary services	
Parasite and disease management	
Pastures management	
Hey making	

Appendix 2: Variance Inflation Factors

Variable	VIF	1/VIF
Job of head of household	1.4	0.713414
Access to information	1.29	0.775904
Herd size	1.25	0.798916
Group membership	1.25	0.802403
Household size	1.23	0.815627
Gender of household head	1.15	0.870987
Access to credit	1.14	0.873638
Distance to market	1.1	0.906936
Education of household head	1.09	0.915001
Age of household head	1.09	0.918112
Contract sell	1.06	0.946844
Access to extension	1.05	0.950256
Land	1.04	0.962041
Mean VIF	1.16	

Appendix 3: Pearson Correlation Matrix

VARIABLES	art use	Extension	Age	Gender	Credit	Education	Hsize	Land	Job	Informa	Group	Mrkt	Herd size	Contract
artificial use	1													
Extension service	0.2509	1												
Age	0.1283	0.0166	1											
Gender	-0.0255	-0.0522	-0.0694	1										
Credit	-0.0438	-0.0237	-0.0118	0.1515	1									
Education	0.1588	0.0284	-0.1833	-0.1002	-0.015	1								
Household Size	-0.0818	-0.033	0.1167	-0.0689	0.0332	-0.1351	1							
Land	0.342	0.1326	0.0644	0.0045	-0.031	0.0491	-0.018	1						
Job	-0.3103	-0.1106	-0.1686	-0.049	0.1582	0.0612	-0.0824	-0.12	1					
Access to Information	-0.201	0.0579	-0.1067	-0.1657	0.0641	0.1544	-0.0607	-0.06	0.39	1				
Group membership	-0.2428	-0.0284	-0.0325	0.1994	0.3086	0.0605	0.0144	-0.06	0.23	0.1715	1			
Distance to market	-0.0816	0.0134	0.078	-0.0088	-0.106	0.007	-0.0026	0.029	-0.2	-0.041	0.0334	1		
Herd size	-0.098	0.0452	0.0645	-0.1121	0.0747	-0.0676	0.3813	-0.04	0.12	0.039	0.088	-0.036	1	
Contract sell	0.0729	0.0157	-0.0162	0.0173	0.0619	0.0176	0.0059	-0.02	0.03	-0.093	0.0901	-0.116	0.12	1

Appendix 4: Descriptive Statistics for Selected Continuous Variables

Variables	Observations	Mean	St. Deviation	Min	Max
Land	398	10.68034	19.16520	0.5	120
Distant	398	7.101021	2.058634	5	15
Age	398	43.6388	14.19883	18	80
Total Household	398	6.193222	2.698248	1	12
Meal	398	2.843455	0.297795	1	3
Cattle have	398	7.584898	13.53687	1	30