FACTORS INFLUENCING ADOPTION AND INTENSITY OF USE OF ARTIFICIAL INSEMINATION TECHNOLOGY AMONG FARMERS IN ALEGO-USONGA SUB-COUNTY, SIAYA COUNTY, KENYA

BY

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DECLARATION

Declaration by the Student

This thesis is my original work and has not been presented for a degree in any other University.

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DEDICATION

This Thesis is dedicated to my family for their selfless financial support, encouragement and moral support during the period of my study.

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ABSTRACT

Artificial Insemination (AI) is a breeding technology that can be used in dairy cows to help in upgrading of the local breeds within their own setting to increase milk production. Despite the positive benefits of A.I technology such as the ability to get superior genes with a capacity to improve milk productivity, the adoption level has been low in Alego-Usonga Sub-county where an observable peak of 40.72% A.I service in 2016 was realized among smallholder dairy farmers. Therefore this study aimed at establishing the factors influencing A.I technology adoption and intensity among smallholder dairy farmers in Alego-Usonga Sub-County. The specific objectives were to determine the effect of Social, Economic, Technical and Institutional factors on adoption of AI technology among smallholder dairy farmers in Alego-Usonga Subcounty. The Innovation Diffusion Theory guided this study. The study area was Alego- Usonga Sub-County, Siaya County, Kenya. The study population was all smallholder dairy farmers in Alego- Usonga Sub-County. Cross-sectional survey design was used in this study. Multistage random sampling techniques was employed to sample 378 dairy farmers from a population of 22965 dairy farmers from the six wards. Structured questionnaires were used to collect primary data. Double Hurdle Model was used analyze factors influencing adoption and intensity of AI technology. Multivariate data analysis was performed using STATA Software. Results of the probit model showed that age of the respondents (β=0.253, p=0.013), education level (β=0.201, p=0.000), experience (β=0.121, p=0.041), milk sales (β=0.001, p=0.003), AI cost (β=0.542, p=0.008), worker's skill on heat detection (β=0.198, p=0.047), semen type (β=0.345, p=0.000), AI reliability (β=1.862, p=0.000), and availability of the inseminator (β=0.85, p=0.000) positively and significantly influenced AI technology adoption in the study area. On the other hand, only training on livestock production (β=-0.496, p=0.028) negatively and significantly influenced AI technology adoption in the study area. Results of the truncated regression showed that age of the respondents (β=0.05, p=0.000), education level (0.042, p=0.000), experience (β=0.058, p=0.001), and training on livestock production (β=0.056, p=0.009) positively and significantly influenced the intensity of AI technology use in the study area. On the other hand, group membership (β=-0.038, p=0.03), and availability of the inseminator (β=-0.048, p=0.024) negatively and significantly influenced the intensity of AI technology adoption in the study area. The study recommends the introduction of adult learning sessions for farmers in a bid to improve their literacy levels. There is need to conduct training needs assessments before the trainings are carried out so as to capture the farmers' interest together with the environment. Farmers should also enhance the skills of their workers by allowing them also to attend trainings. The government should step in by subsidizing the cost of AI and funding trainings and workshops as this will encourage many farmers who were unable to take up the technology to adopt it.

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LIST OF ABBREVIATIONS AND ACRONYMS

AI – Artificial insemination

ASDSP- Agricultural Sector Development Support Programme

CAIS – Central Artificial Insemination Services

CIDP – County Integrated Development Plan

FAO – Food and Agriculture Organization

FTAI – Fixed Time Artificial Insemination

GDP – Gross Domestic Product

GoK – Government of Kenya

ILRI – International Livestock Research Institute

KAGRC – Kenya Animal Genetic Resource Centre

KDB – Kenya Dairy Board

KNAIS – Kenya National Artificial Insemination Services

KNBS – Kenya National Bureau of Statistics

KPHC – Kenya Population and Housing Census

LCBA – Limuru Cattle Breeders Association

USAID – United States Agency for International Development

OPERATIONAL DEFINITION OF TERMS

Adoption: is defined as the decision to make full use of an innovation, an innovation is an idea, practice or objected that is perceived to be new (Rogers 1971).

Artificial insemination: Artificial insemination (AI) is the process of introducing semen into the reproductive tract of a female using instruments for conception purpose (Shehu *et al.*, 2010).

Agricultural technology: is described as equipment, genetic material, farming techniques, and agricultural inputs that have been developed to improve the effectiveness of agriculture (Ruzzante *et al.*, 2021).

Fixed Time Artificial Insemination: As the name suggests, the time to inseminate the animal is predetermined removing the need and cost associated with observation for heat signs (Mwai *et al.*, 2020).

Intensity: Frequency of A.I use by smallholder dairy farmer per year. In this study intensity refers to the number of times one has used AI services per cow in the past five years.

CHAPTER ONE: INTRODUCTION

1.1 Background of the Study

The livestock industry is crucial to achieving food security and the sustainability of the global economy. The livestock sub-sector in Kenya contributes over 30% of the farm gate value of agricultural commodities, about 10% of the national Gross Domestic Product (GDP) and at least 50% of the agricultural GDP (KALRO, 2024). Further, Approximately 50% of the labor force in agriculture is employed in this sector. The primary challenge for the livestock sector, particularly the dairy sub-sector, is meeting the increasing demand for livestock products using technology in a way that the natural resource base can be sustained without environmental harm (Roe, 2009; Amede *et al.*, 2011). Additional challenges include the spread of reproductive diseases, poor conception rates, social issues from sharing bulls, lack of control over progeny quality, poor feed quality and insufficiency, limited financial resources, inadequate veterinary support, and poor performance of dairy breeds (Roe, 2009; Amede *et al.*, 2011; Gahakwa *et al.*, 2014).

According to Kimunya (2014), the use of technologies in the livestock sector increases productivity, lower the risk of disease, and ensures environmental sustainability in productive areas. There are a number of reproductive technologies available to transfer desirable genetic materials such as artificial insemination, embryo transplant, and vitro fertilization, of which only artificial insemination (AI) is the most commonly used technique in developing countries including Kenya. Particularly used as a reproduction method in dairy farming, AI provides significant economic contributions to milk production and to farmers by genetically improving animals (Howley *et al.*, 2012). The advancement and application of artificial insemination have significantly transformed cattle production

and genetic enhancement, especially within the dairy industry in developed nations (Henning *et al.*, 2010).

Artificial Insemination is the process by which semen is artificially introduced into the female reproductive tract for the purpose of conception (Shehu *et al.*, 2010). For the purpose of this research the study will dwell on the frequency of artificial insemination by the AI expert in consultation with the farmer. This breeding technology helps in increasing productivity and hence income in the dairy sector, since the selection of productive semen is done and used, thus promoting upgrading, and if done well then productivity of the animals is expected to increase positively within their own environment. This will lead to an improved quality of life through enhanced incomes and greater productive efficiency.

Driven by ever-increasing human demand, milk production is a key target within the dairy sector, with AI technology playing a vital role in boosting yields. Milk contributes substantially to the global economy, accounting for 27% of the value added by livestock and 10% of the total agricultural value added (FAO, 2016). Furthermore, it represents 14% of global agricultural trade. Looking ahead, world milk production is projected to grow by 177 million tons by 2025, representing an average annual growth rate of 1.8% over the next decade. This growth is fueled by increasing per capita consumption of dairy products, projected to rise by 0.8% to 1.7% annually in developing countries and between 0.5% and 1.1% in developed countries (FAO, 2016).

Cows are the most prevalent dairy animal. While farmers in developing countries typically keep just two or three cows, the scale of dairy farming is much larger in developed nations. For instance, the average dairy herd size is around 90 cows in the UK and 300 in the US (FAO, 2016). The average milk production per cow in Kenya is estimated at 8 to 10 litres per day, with a lactation yield of between 200 and 2,400 litres. These figures are

significantly lower than the global average of 40 litres per day and up to 14,000 litres per lactation. This disparity is attributed to inefficient breeding services, inadequate management practices, and insufficient extension and advisory services.

Heat synchronization of heifers and cows was tried in Siaya County amongst other counties, with the Government of Kenya collaborating with ILRI to upgrade the local zebus using fixed time artificial insemination (FTAI). This initiative saw the increase in the number of artificial inseminations in Alego-Usonga sub-County with a peak being witnessed in 2016 as presented in table 1.2. Despite the potential of AI technology to upgrade local zebus through selective breeding and meet growing milk demand, its use has been declining.

Several studies have explored the drivers of AI technology in different contexts, highlighting the complex interplay of socio-economic, institutional, and technical factors (e.g. Gebre *et al.*, 2022; Ingabire *et al.*, 2018; Bayan, 2018; Mwanga *et al.*, 2019). These factors can include farmer characteristics (age, education, and experience), access to credit and extension services, cost of

AI services, availability of liquid nitrogen, infrastructure, and cultural beliefs (Ayantunde *et al.*, 2008). Understanding these factors is crucial for designing and implementing effective interventions to promote AI technology adoption and maximize its impact on livestock productivity.

In Alego-Usonga Sub-County, while livestock keeping is a common practice, there is a need for more in-depth research to understand the specific constraints hindering the wider and more effective use of AI technology. Previous studies conducted in other regions of Kenya may not fully capture the unique context of Alego-Usonga, which might have distinct socio-economic, environmental, and cultural characteristics. Therefore, a

comprehensive analysis of the factors influencing AI adoption and intensity of use within this specific sub-county was essential. This study sought to address this gap by investigating the socio-economic, technical, and institutional that influenced farmers' decisions to adopt and consistently utilize AI technology in AlegoUsonga sub-County.

1.2 Statement of the Problem

The dairy sub-sector in Kenya plays a crucial role in the economy in terms of GDP and food contribution. The Kenyan dairy sub-sector accounts for about 15% of the total agricultural sector's gross domestic product (GDP) and aims to play a significant role in achieving the 10% economic growth stipulated in Kenya's Vision 2030 blueprint document (Kwamboka, 2022). Further, the sub-sector is significant in contributing to poverty alleviation and food and nutritional security in both rural and urban areas (Nyaga *et al.*, 2023).

Milk productivity in Kenya is low estimated at 7-9 litres per cow per day attributed to genetics and poor feeding among other poor animal husbandry practices (Onsare, 2020). Moreover, in Siaya, milk production is significantly lower, averaging 3.4 litres for grade dairy herds and 2.4 litres for zebus. To improve this, upgrading local breeds through artificial insemination (AI) is crucial. AI offers significant potential to enhance livestock breeds, productivity, and farmer incomes by disseminating superior genetic material. Despite this potential, AI adoption and usage among farmers in the area remain suboptimal, hindering the full realization of its benefits and perpetuating low livestock productivity.

While some studies have explored AI technology adoption in other regions, there is a lack of specific understanding regarding the factors influencing adoption and intensity of use within Alego-Usonga sub-County. This knowledge gap makes it difficult to design and

implement targeted interventions to promote AI uptake and enhance livestock productivity in the area.

Therefore, this study analyzed the socio-economic, technical, and institutional factors influencing both the adoption and intensity of AI technology among smallholder dairy farmers in the Alego-Usonga sub-County.

1.3 Objectives of the Study

1.3.1 General Objective of the Study

To assess factors influencing adoption and intensity of use of A.I technology among smallholder dairy farmers in Alego-Usonga Sub-County, Siaya County in Kenya.

1.3.2 Specific Objectives of the Study

i. To assess the impact of social factors such as age, gender, education level, farmers experience in dairying, and group membership on the adoption and intensity of AI technology among smallholder dairy farmers in Alego-Usonga sub-County.

ii. To analyze the effect of economic factors such as herd size, milk sales, cost of A.I technology, and cost of bull on A.I technology adoption and intensity among smallholder dairy farmers in Alego-Usonga sub-County.

iii. To evaluate the influence of technical factors such as worker's skill on heat detection, semen type, AI reliability, and supplements use on A.I technology adoption and intensity among smallholder dairy farmers in Alego-Usonga sub-County.

iv. To examine how institutional factors such as extension access, trainings, support services, and availability of Inseminator on A.I technology adoption and intensity among smallholder dairy farmers in Alego-Usonga sub-County.

1.4 Research Hypotheses

H_{01}: Social factors (age, gender, education level, experience, and group membership) do not significantly influence AI technology adoption and intensity among smallholder dairy farmers in Alego-Usonga sub-county.

H_{02}: Economic factors (herd size, milk income, cost of A.I technology, and cost of bull) do not significantly affect AI technology adoption and intensity.

H_{03}: Technical factors (worker's skill on heat detection, semen type, AI reliability, and supplements use) do not significantly influence the adoption and intensity of AI technology.

H_{04}: Institutional factors (extension access, trainings, support services, and availability of inseminator) do not significantly affect the adoption and intensity of AI technology.

1.5 Justification for the Study

The study is crucial as it addresses the key factors influencing the adoption and intensity of Artificial insemination (AI) technology among small-scale dairy farmers in Alego-Usonga subCounty. AI is a transformative technology that can significantly improve livestock productivity and enhance the livelihoods of small-scale dairy farmers in the study area. However, the adoption of AI technology in rural Kenya remains low, and understanding the underlying factors, such as age, education, experience, cost, and access to extension services, can help identify barriers and opportunities for improvement.

By focusing on the specific context of Alego-Usonga, this study provides valuable insights into the local challenges and offers targeted recommendations that can support the adoption of AI technology, increase dairy productivity, and promote economic development in the area.

Additionally, the findings contribute to the broader conversation on agricultural technology adoption in sub-Sahara Africa, offering relevant lessons for areas with similar agricultural landscapes.

1.6 Significance of the Study

Undertaking a study on factors that influence AI technology adoption and intensity is important for policymakers, agricultural extension officers, and farmers in promoting the use of AI technology to improve livestock productivity and genetic diversity. The findings of this study can provide evidence-based information to policymakers in the Ministry of Agriculture and related agencies. This information can be used to formulate effective policies and strategies that promote the adoption of AI technology among farmers. By understanding the specific factors that influence adoption, policymakers can design targeted interventions, such as training programs, subsidies, and improved access to AI services, to address the challenges faced by farmers and create an enabling environment for AI technology uptake.

Further, the study can assist extension service providers in tailoring their services to meet the specific needs of farmers. By understanding the factors that influence adoption, extension officers can provide targeted training and support to farmers, addressing their concerns and enhancing their knowledge and skills in using AI technology effectively. This can lead to increased adoption rates and improved livestock productivity.

Additionally, the study is useful to the farmers as it can enable them make informed decisions about their livestock breeding practices. The study can empower farmers to adopt AI technology effectively, leading to improved livestock productivity, increased productivity, and enhanced livelihoods.

Finally, the study serves as a foundation for future research on AI technology adoption in the region and beyond. By identifying key factors influencing adoption, the study can guide further investigations into specific areas of interest, such as the impact AI technology on livestock productivity, farmer incomes, and the environment. This can contribute to a deeper understanding of the role of AI technology in livestock development and inform future interventions.

1.7 Scope and Limitations of the Study

This study was limited to assessing factors influencing adoption and intensity of use of artificial insemination technology (AI) among small-scale dairy farmers. The study was conducted on small-scale dairy farmers in Alego-Usonga sub-County, Siaya County, Kenya. The researcher was faced with the following shortcomings: reaching all the small-scale dairy farmers was not an easy task, hence enumerators were employed; despite the advantages of using interviews in data collection, the technique was regarded as costly and time consuming, hence the researcher countered this by setting time frames within which interviews were conducted in a bid reduce costs and save time.

CHAPTER TWO: LITERATURE REVIEW

2.1 Concepts of the Study

2.1.2 Concept of Artificial Insemination Technology

Agricultural technology, according to Ruzzante *et al.* (2021) is a broad term that is used to describe equipment, genetic material, farming techniques, and agricultural inputs that have been developed to improve the effectiveness of agriculture. Effectiveness refers to an equally broad range of productivity, health, welfare, and sustainability outcomes (Ruzzante *et al.,* 2021). The adoption and widespread use of advanced agricultural technologies are crucial for reducing poverty and enhancing food and nutritional security in developing countries (Barrett *et al.*, 2010). The use of modern breeding technologies such as AI, can enhance productivity by improving reproductive outcomes and, consequently, genetic composition (Msalya *et al.*, 2017; Sartori *et al.*, 2016).

Artificial Insemination, as defined by Morrell (2011) and Patel *et al.* (2017), is the manual placement of semen into a female's reproductive tract by a technique other than natural mating. AI is widely recognized as the fastest and most dependable method for sharing advancements in genetic resources conducted across various regions worldwide, ultimately benefiting humanity (Howley *et al.*, 2012; Mugisha *et al.*, 2014; Galina *et al.*, 2016). Artificial insemination was initially created to manage the spread of animal diseases, by eliminating the need to transport live animals carrying potential pathogens to other units for mating and by preventing direct physical contact between individuals (Kubkomawa, 2018). To enhance the low productivity of indigenous Zebu cattle, selecting the most promising breeds and crossbreeding them with highyielding exotic cattle has been deemed a practical solution (Mekonnen. *et al.*, 2010).

Similarly, Sarakul *et al.* (2011) stated that genetic enhancement of cattle is crucial for economic reasons, particularly milk production. AI technology plays a key role in a comprehensive strategy to boost the profitability and sustainability of dairy cattle operations, thereby improving the livelihoods of farmers. While many farmers understand the benefits of AI and express a preference for its adoption, research from Africa indicates that only a small number of farmers actually utilize the technology (Tefera, 2013; Mugisha *et al.*, 2014; Tebug *et al.*, 2014).

Consequently, AI adoption rates are low not only in Africa but also in other global regions (Martinez-Garcia *et al.*, 2016; Howley *et al.*, 2012).

Advantages of artificial insemination include enhanced efficiency. Bulls can deposit more semen into female reproductive tracts during mating. However, this process is physically demanding, which reduces their reproductive effectiveness as they age. Collecting semen allows one bull to serve numerous cows beyond its reproductive lifespan (Patel *et al.*, 2017). Additionally, transporting semen across distances is easier than moving entire bulls, facilitating broader genetic diversity (Patel *et al.*, 2017). Artificial insemination also boosts genetic selection potential by enabling a few males to father many offspring, eliminating the need for multiple males on farms. Offspring from artificial insemination can participate in progeny testing to accurately assess male genetic potential and mitigate inbreeding risks (Patel *et al.*, 2017).

The method increases safety for both farmers and animals by reducing risks associated with large, aggressive male animals during natural mating, which can lead to accidents and injuries (Patel *et al.*, 2017). Furthermore, artificial insemination reduces disease transmission compared to natural mating, as it prevents the spread of infectious genital

diseases like Trichomoniasis and brucellosis (Mohammed, 2018). Only disease-free males are selected for semen collection, ensuring safer breeding practices (Patel *et al.*, 2018). Moreover, artificial insemination allows breeding to continue even if sires have physiological or behavioral issues. Advancements in technology also enable the use of sexed semen, which determines offspring sex, thereby increasing the number of desired female animals on farms and enhancing overall productivity.

Pregnancy success rates are a crucial measure of artificial insemination (AI) effectiveness in dairy cattle, and they are impacted by a number of factors pertaining to the cow, the farm, and the AI technician. One important consideration is the breed. Exotic breeds typically have higher conception rates than local or crossbreed breeds, mostly because local breeds can be difficult to detect heat in, and because exotic breeds receive more attention from farmers, which makes heat detection easier and consequently increases conception rates (Howlader *et al.*, 2019; Woldu *et al.*, 2011).

The age of the cow is another significant consideration. AI conception rates often rise with age but fall with advanced age. Compared to older cows, first parity cattle, who have only given birth once, usually have greater conception rates. Because older cows have lower conception rates, this has a direct impact on AI performance (Howlader *et al.*, 2019; Mufti *et al.*, 2010). Furthermore, AI performance may be considerably impacted by a retained placenta. A uterus devoid of pathogens is necessary for a successful fertilization. Retained placentas can result in metritis, which can hinder implantation even in cases of fertilization. This can have an impact on conception rates and the effectiveness of AI.

Additionally important is the timing of insemination. Relative to the cow's heat cycle, insemination has a big impact on the success of conception. When the ovum gets at the fertilization location, healthy living sperm should be there as well to maximize conception

rates. Successful conception and enhanced AI performance depend on accurate ovulation prediction utilizing standing heat (Mufti *et al.,* 2010). Another important factor is nutritional status. Cows' bodily condition score and their capacity to produce heat are influenced by their dietary status. When given AI, cows with higher body condition scores come into heat more quickly and have greater conception rates than cows with lower body condition scores; hence, the AI performs better (Yehalaw *et al.,* 2018). Furthermore, the effectiveness and functionality of AI depend heavily on precise heat detection. Inaccurate detection reduces milk output by encouraging repeated breeding and longer calving intervals. This problem is especially common on farms where a substantial number of cows depend on secondary estrous signals (Jemal & Lemma, 2016; Mufti *et al.,* 2010).

Proper thawing of semen before insemination is necessary, as spermatozoa are inactivated at low storage temperatures. When sperm are thawed at the ideal temperature range of 37°C to 40°C, effective fertilization can occur. Spermatozoa can be destroyed by improper thawing temperatures, which will lower the likelihood of conception (Mufti *et al.,* 2010). Lastly, conception rates are influenced by the site of semen deposition in the reproductive canal. AI technicians have higher success rates with conception when they deposit semen in the uterus as opposed to the cervix (Macpherson, 1968). This technique highlights the differences in technicians' AI performance.

Despite the merits there are also hindrances to the use of the technology which include its cost, which some farmers perceive as higher compared to natural mating with a bull, despite its well known advantages (Patel *et al.,* 2017). Additionally, artificial insemination can lead to extended calving intervals due to challenges in heat detection, which are not typically encountered with natural mating (Patel *et al.,* 2018). The method also impacts genetic diversity. Unplanned use of artificial insemination may contribute to genetic

erosion and even breed extinctions (Pilling *et al.,* 2007). Furthermore, there is a risk of spreading pathogens through semen. Some males can shed viruses in semen without showing clinical signs of disease, potentially transmitting infections during artificial insemination procedures.

Despite benefits associated with AI such as improving productivity of the herd, this technology has had low adoption rates in sub-Saharan Africa (SSA) (Mwanga *et al.,* 2019; Abraha *et al.,* 2020; Abot, 2020). Within East Africa, use of AI is most widespread in Kenya but national coverage is quite low compared with AI use in India (Ojango, 2016). AI has been in some instances used to speed up crossbreeding in Tanzania (Kyomo and Kifaro, 2005). Temba (2011) reported a low AI adoption rate, with less than 40% of dairy farmers using this technology in Kinondoni District, Tanzania. The reasons for the low uptake of AI by farmers have never been clearly established across the main dairying countries in Africa. Available evidence suggests that this may be due to various infrastructural and technical challenges (Temba, 2011).

2.1.2 Intensity of AI technology

While adoption studies provide valuable insights, understanding the intensity of AI use is crucial for maximizing its impact. Intensity of artificial insemination (AI) technology use refers to the frequency and scale at which AI is utilized within a herd. The intensity of AI use can be assessed by considering the AI service utilization rate (number of AI services per cow per year), the proportion of inseminated cows (percentage of eligible cattle receiving AI), repeat insemination frequency (number of AI attempts per conception), and adoption at the farm level (consistent use of AI as the primary breeding method).

In Africa, AI technology remains underutilized, with variations in intensity across different regions and production systems. For instance, Omondi *et al.* (2017), and (Varisanga, 2024)

document that coverage of artificial insemination in Africa remains low, with less than 2% of breedable females inseminated, with very low level of efficiency. This low utilization is attributed to various factors, including infrastructural challenges, management issues, financial constraints, poor heat detection, and improper timing of insemination. In Ethiopia, AI coverage is estimated at 26% of breedable females, with significant variations between urban and rural areas (Temesgen *et al.,* 2021). In Kenya, the adoption rate of AI services among smallholder livestock farmers in dryland production system is approximately 13.3% (Abot, 2020).

The intensity of AI use is even lower in arid and semi-arid regions due to infrastructure limitations and the high cost of semen. Further, poor heat detection skills and delayed insemination reduce AI success rates, limiting the number of insemination performed per animal. Farmers with high-yielding breeds are more likely to use AI intensively to maintain genetic progress (Mekonnen *et al.,* 2010). AI use intensity is higher in areas where governments provide subsidized services or incentives for genetic improvement. Further, Gebre *et al.* (2022) reports a low intensity score of artificial insemination among households in Ethiopia.

While AI is recognized as key technology for genetic improvement and productivity enhancement, its intensity of use is influenced by multiple factors, including service availability, cost, farmer awareness, and policy support. The presence of AI service providers significantly impacts utilization rates. For instance, regions with limited AI technicians report lower intensity of AI use as compared to areas with adequate service providers. The affordability of AI services affects how frequently farmers use them. For instance, high cost discourage repeat inseminations, leading to lower intensity (Ojango *et al.,* 2017). A study by Abot (2020) discovered an influence of education level of the

household head, distance to AI centre, household size, and access to information on market prices, distance to market, and dishonesty from the service provider on the intensity of artificial insemination. Extension services access and training also impacts the extent of using AI by creating more awareness and enhancing farmers' knowledge and skills (Gebre *et al.,* 2022).

2.2 Overview of AI Technology

The rising demand for livestock products necessitates intervention measures to manage and sustain production. One key strategy is the use of artificial insemination (AI) in breeding, as livestock productivity depends on genetics, health, and husbandry. AI is considered as one of the most effective ways of disseminating superior genes for improving dairy production, shortening calving intervals and fertility improvements in developed countries (Stevenson, 2014). AI remains the most commonly adopted breeding technique by small-scale dairy farmers in developing countries possibly due to its relative simplicity, high success rate and low cost (Vishwanath, 2003 and Quddus, 2013). This technology is also well utilized in countries of Africa like South Africa and Kenya (Omondi *et al.,* 2017).

Globally, 110 million first inseminations were recorded in 1998 of which more than 50% were performed in the Far East. In Europe close to 38million females (34%) and North America approximately 11 million (1%) have been inseminated. South America and Near East have inseminated more than one million and Africa approximately 0.9 million (0.8%) (Thibier & Wagner, 2002). In Asia AI coverage stands between 1% and 5%, except for countries like China (12.6%), Afghanistan (20.2%) and Indonesia (23.1%), smaller countries like Hongkong, the Republic of Korea and Singapore almost 100% of the breedable females are inseminated (Chuppin and Schuh, 1993).

A.I was first performed in Kenya by Dr. J. Anderson in 1935, and was confined to semen collection from bulls on individual farms for use on cows in the farms from which it was collected, to combat the epivag disease and other infectious diseases. Dr. Anderson revealed that over 35%of bulls tested were sterile, thus emphasizing the use of A.I. In Kenya the first A.I scheme was set up in 1941 based on community bull scheme followed by a scheme operated by the Limuru cattle breeders association (LCBA) in 1942 that continues to date linked to the Kenya. National Artificial Insemination Service Controlled by the Kenya national artificial Insemination Board; chaired by the director of veterinary services.

In Kenya, the Kenya Animal Genetic Resource Centre (KAGRC) formerly CAIS is charged with semen production. The station has bulls from the four dairy breeds, Ayrshire, Friesian, Guernsey and Jersey. Over 700,000 doses of semen are annually produced mainly for use in the national A.I service schemes, 1% is exported and 3% is sold to private and Government farms. Semen used by farmers in Kenya is also imported from farms overseas in UK, USA, Australia, and New Zealand among others. Provision of AI services is privately done by technicians from approved AI training centers or by qualified veterinarians. Many cooperative societies also offer AI services to their member through their trained inseminators.

By 1958, farming schemes existed, but adoption rates remained low. The use of A.I declined significantly in 1963 due to subdivision of large farms and rising costs, leading to a drop in sales. However, in 1964, the established settlement farms increased the demand for dairy stock, prompting a rise in semen sales. As a result, AI services were subsidized to support the growing demand. Due to partly declining genetic base the dairy sector experienced reduced productivity. Government-backed artificial insemination (AI) service

facilitated the widespread adoption, recording 579,000 insemination in 1979. However, between 1979 and 2002, the number dropped significantly to 68,339 inseminations. With the revival of the dairy industry, AI services increased from 68,339 in 2002 to 233,384 inseminations in 2012. Following the government's withdrawal from the direct provision of artificial insemination (AI) services in 1992, AI usage declined nationwide. Due to the high cost and limited availability of AI services, many farmers reverted to using bulls for breeding.

In Siaya County, the dairy sector experienced changes following devolution, with grants provided to farmer groups in the form of dairy cattle and equipment. However, these groups faced high livestock mortality rates. Despite interventions from partners such as GIZ, Heifer International, ILRI, USAID, World Vision, and PLAN International, focusing on farmer training and policy development, milk production remained low. Farm sizes in the county vary, averaging 0.6 hectares for small-scale farms and 7.0 hectares for large-scale farms. The dairy cattle population is predominantly zebu cattle (74%), producing an average of 2.4 liters of milk per day (Siaya Dairy Policy, 2019). The county's total dairy population is estimated at 7,000 heads, contributing 26% of total milk produced and 81% of total marketed milk. Productivity for grade cattle is slightly higher, averaging 3.4 liters per day, or approximately 1,039 liters per year per cow (Siaya Dairy Policy, 2019).

Table 2.1: Summary of Siaya Cattle Population, Milk Production and Scale

	GRADE CATTLE	ZEBU CATTLE	TOTAL
Cattle population (heads)	7024	352,299	359,323
Milk production (million litres)	7.3	20.6	27.9
Percent of total milk produced (%)	26	74	100
Milk scale (million litres)	4.4	1.0	5.4
Percent of total milk scale (%)	81	19	100

Source: Siaya Livestock Production office, (2019)

To meet Siaya County's milk demand, dairy herds must increase their productivity from 1,039 liters per cow per year to 3,484 liters per cow per year. This can be achieved through the application of good management practices and the upgrading of existing livestock to higher yielding breeds. Milk production in Siaya is primarily smallholder-based, with farmers typically keeping one to five cows on 0.5 to 3-acre farms. These farms are concentrated in the high rainfall zones of Gem, Ugunja, and parts of Alego Usonga and Ugenya sub-counties, where mixed farming is practiced. The dairy sector comprises an estimated 3,512 households, contributing 26% of total milk production and 81% of marketed milk in the county.

On average, households in Siaya County keep two dairy cows, producing 3.5 liters per cow per day, with most milk being sold informally (Siaya Dairy Policy, 2019). Medium- and large-scale farmers, who account for less than 1% of total domestic milk production, maintain herds of 20 to 30 milking cows, achieving higher productivity than smallholder farmers. Despite a dairy herd of approximately 7,000 cows, there is a shortage of AI services in the county. The annual number of AI services averages 2,100, except in 2016, when ILRI's Fixed-Time Artificial Insemination (FTAI) interventions temporarily increased AI access. However, 90% of adult female dairy cattle require about 6,400 AI services

annually, resulting in a deficit of 4,360 services per year, based on a total dairy herd population of 7,024. Table 2.2 below presents the distribution of AI services per sub-county in Siaya County.

The Fixed-Time Artificial Insemination (FTAI) intervention was expected to increase the demand for AI services. However, as shown in Table 2.2, a downward trend followed instead. The initial rise in AI use did not sustain beyond the FTAI intervention, indicating underlying challenges. This highlights the need to investigate the factors affecting AI adoption in Siaya County, with a specific focus on Alego Usonga Sub-County, to identify barriers and develop strategies for improving AI uptake among farmers.

Table 2.2: Number of Artificial Insemination Services in Siaya per Sub-county

Year	Bondo	Rarieda	Alego-Usonga	Ugunja	Gem	Ugenya	Total
2013	360	60	450	120	550	65	1,605
2014	354	85	480	186	545	72	1,722
2015	402	84	750	236	520	78	2,070
2016	424	204	1250	358	668	166	3,070
2017	460	102	900	130	592	102	2,286
2018	350	80	780	95	800	65	2,170
Total	2,350	615	4,610	1,125	3,675	548	12,923

Source: Directorate of Veterinary Services, (2019)

Table 2.3: Number of Artificial Insemination – Siaya County – Jan 2019 to June 2024

Period	Breed					Total
	Friesian	Ayrshire	Jersey	Fleckvieh	Guensey	
Jul-23 to Jun-24	465	325	93	19	19	920
Jul-22 to Jun-23	421	294	84	12	16	827
Jul-21 to Jun-22	413	289	81	18	17	817
Jul-20 to Jun-21	399	276	81	7	16	779
Jan-19 to Jun-20	329	230	66	13	14	651

Source: Directorate of Veterinary Services, (2024)

Table shows that the demand for artificial insemination (AI) cattle in Siaya County has been increasing annually. As shown in the table, Friesian and Ayrshire breeds are on high demand in the region. This trend is driven by the rising demand for milk, milk products, and other foods from animal origin. However, the full potential of AI services remains underutilized.

2.2 Factors Influencing Small-scale Farmers Uptake of AI Technology

The adoption of improved breeding technologies by farmers varies widely across different agro ecological and within the same agro-ecological zones being influenced by various technical and non-technical factors (Dehinenet *et al.,* 2014; Korir *et al.,* 2023). Ruzzante *et al.* (2021) notes that scholars have studied numerous motivating factors and constraints to adoption by observing the different behaviors between adopters and non-adopters of technology. Technological, economic, institutional, and individual-specific factors are identified as significant influences on the adoption of technology (Mwangi and Kariuki, 2015). Additionally, cultural, contextual, and policy factors that are not readily observable also play crucial roles in this adoption process (Ruzzante *et al.,* 2021). Numerous factors

influence the adoption of precision agricultural technologies (Tey and Brindal, 2012), particularly artificial insemination (AI). These factors can be categorized into demographic, socio-economic, and location-based factors (Tebug *et al.,* 2014). Simply put, there are farm-related and farmer-related factors that impact AI adoption (Howley *et al.,* 2012). Additionally, factors affecting AI adoption can be divided into fixed and modifiable categories (Galina *et al.,* 2016). This study categorises this factors into four: Social, economic, technical and institutional factors.

2.2.1. Social Factors and AI Technology Adoption

Age is an important factor that influences the probability of adoption of new technologies because it is said to be a primary latent characteristic in adoption decisions (Akudugu *et al.,* 2012). However, literature has it that age may positively or negatively impact on the adoption of these technologies. Younger farmers with higher education levels are inclined to adopt agricultural technologies. Similarly, older farmers with extensive experience in dairy production are more likely to adopt new technologies, unlike their counterparts who remain committed to traditional breeding methods. Abot (2020) established a positive influence of age to the extent of adoption. Kosgei *et al.* (2021) also established that young dairy farmers as opposed to older farmers can easily adopt new AI technology. They can also easily change to other technologies as compared to older dairy farmers who are reluctant to abandon old technologies for ones that are new. In another study, Khainga *et al.* (2015) found age to be negatively associated with adoption decisions because younger farmers are less risk averse and are ready to invest in long term plan due to their age. However, age has also been found to be either negatively correlated with adoption, or not significant in farmers' adoption decisions.

The adoption of agricultural innovations, including AI, often hinges on social, economic, and cultural factors, with gender roles playing a pivotal role. Women's participation in agriculture varies widely across different regions, influenced by traditional gender roles, access to resources, and policy frameworks. Studies indicate that women generally have less access to financial resources than men. A study by Mwambene *et al.* (2014) established a low adoption rate of exotic cow breeds in rural Tanzania attributed to social influences and low resource input available to them. This disparity can affect their ability to invest in AI technology, which requires initial capital for equipment and ongoing costs for services. Women often have lower levels of formal education and access to agricultural extension services, which can limit their awareness and understanding of AI technology. Training and education programs tailored to women can significantly enhance AI adoption rates among female farmers. Women are more likely to be livestock adopters than men due to their high participation in extension activities.

Temba (2011) established a difference between adopters and non-adopters with respect to sex of respondent was found to be statistically significant. In this case women dominated in adoption of AI technology. Kinyangi (2014) in his study found gender to have insignificant influence on adoption of agricultural technologies in Kakamega North sub-county. Also, Lochampa (2019) found there were more male-headed households (71.9%) than female-headed households (28.1%), and further established no influence of gender on the adoption AI in Nyamira County. a study by Fentaw (2017) revealed that female household head participants were less likely to adopt dairy technologies possibly because female households resource poor and less accessible to extension services so as to participate on technological innovations.

Education in many instances has been associated with adoption of a particular technology, and thus the level of education may determine the choice of the farmer to adopt a technology or not. Highly educated farmers are likely to easily adopt this technology as compared to the less educated ones. According to Abot (2020) farmers with formal education can easily comprehend and process information on agricultural technologies such as AI. Further, Galina *et al.* (2016) and Okello *et al.* (2021) note that educated and informed farmers are able to identify the health and productivity related factors such as signs of estrus or deworming signs which is necessary to call for AI services or minimize the cost of AI services. Studies by Lochampa (2019), Temba (2011), Tefera *et al.* (2014), and Bayan (2018) discovered a positive influence of education level on the extent of AI adoption. It is believed that education enables farmers perceive, interpret and respond to new information faster (Matata *et al.,* 2010). Contrary, Abot (2020) found out that education level had a negative effect on the extent of AI adoption, 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. Mal *et al.* (2012) established a negative correlation between education and intensity of adoption and links the finding to farm enterprise diversification. They state that educated farmers balanced land usage with other enterprises. Moreover, Omondi *et al.* (2017) found that more literate farm households and those keeping exotic cattle derived high utility from AI and were willing to pay more for AI and even to repeat the use of AI should conception fail after the first attempt.

Being a member or affiliated to a certain group may have an influence on whether to adopt or not adopt this technology. Group membership can act as a channel for information dissemination and influence the decision-making process of individual farmers (Rogers, 2003). Additionally, these groups provide access to resources, training, and support

services, reducing the perceived risks and costs associated with AI (Davis & Negash, 2007). Studies on dairy cooperatives in India show a higher adoption of AI among members compared to non-members (Kanu *et al.,* 2014).

Adoption is influenced by participation in farmers-based groups and social networks (Lochampa, 2019). Farmers meet at social functions and discuss issues of concern, learn from each other and knowledge is carried from one community to another (Kwadwo and Kristin, 2009). Similarly, Akin-Kara (2019) reported that a group membership had a positive impact on AI adoption. In contrast, Abot (2020) found that group associations or memberships negatively impact AI adoption, attributed to the fact that, most of the decision regarding livestock are made by men and these informal groups are largely female enterprises.

Farming experience encompasses the practical knowledge and skills that farmers accumulate over time. This experience can affect their decision-making processes, openness to new technologies, and ability to implement complex agricultural practices. Highly experienced farmers are more likely to adopt new technologies like the A.I technology compared to new farmers or less experienced ones. Experience enriches the farmer on the major production aspects such as a sound knowledge of major practices (Namwata *et al.,* 2010). Furthermore, Temba (2011) established that adoption of AI technology is associated with number of years in dairying. This means those who have been in the dairy industry for long are more likely to adopt the technology. Further, Sharma *et al.* (2020) Contrary, Ingabire *et al.* (2018) established a negative influence of farming experience on the adoption of AI technology. Also, Kosgei *et al.* (2020) discovered that a unit increase in the years of experience in dairy farming of the household head resulted in the marginal effect of adoption of the vaccination regime technology. Bayan (2018) also

found a non-significant influence of experience on the extent of AI adoption. However, a study by Korir *et al.* (2023) reported that farmers of workers with no experience were less likely to have adopted multiple dairy technologies.

2.2.2 Economic Factors and AI Technology Adoption

Herd size plays a significant role in AI technology adoption, with farmers owning larger herd size more likely to use AI due to cost-effectiveness, access to resources, and better breeding management. Farmers with larger herds benefit more from AI because the cost of training, equipment, and semen storage can be spread over many animals, reducing per unit costs. Smallholder farmers with small herds may find AI expensive and may not see immediate financial returns and hence may opt for natural bull service. Studies have shown that herd size can significantly impact a farmer's decision to adopt AI technology. For instance, a study by Okello *et al.* (2021) reported that number of cows owned has a positive effect on the decision by smallholder farmers to utilize artificial insemination. However, a study conducted by Herana and Kumari (2017) found that herd size had a negative statistical significant effect on the adoption of AI technology suggesting that farmers with smaller herds are less likely to adopt AI, possibly due to the higher per-animal costs and perceived risks associated with the technology. Gebre *et al.* (2022) reports a positive influence of number of hybrid cattle on AI technology adoption and intensity due to the fact that farmers with hybrid cattle have more knowledge about the importance of hybrid cattle and are encouraged to use AI intensively. A study by Mwanga *et al.* (2019) revealed a positive association between farmers with small herd size and AI adoption.

Further, they report that farmers with large herd size were less likely to use AI services. Similarly, Akin and Kara (2019) found that number of cross- and purebred cattle has a positive effect on the willingness of the farmers to employ AI in Turkey.

High milk sales lead to increased income for dairy farmers. This increased income can make farmers more willing and able to invest in AI technology. AI can improve the genetic quality of their herd, leading to higher milk yields and potentially even greater profits in the future. Wealthier, more stable households tend to adopt agricultural technologies compared to middle- and lower-income households. Household income is considered an important factor in the decision to adopt livestock technologies (Barry, 2005). A study by Kaaya *et al.* (2005) reported that total milk production and milk sales were positively associated with adoption and use of AI technology. Similarly, a study Akin and Kara (2019) reported that milk sales had a positive effect on the use of AI in Turkey. Wambura (1988) found out that young, richer and better educated farmers had higher extension contacts than poor, older and less educated farmers. Also, Temba (2011) established that the difference between adopters and non-adopters with respect to income levels was highly significant. This means that adoption is influenced by level household income. Furthermore, Kinyangi (2014) found in his study that income affected adoption of agricultural technologies in Kakamega North Sub County. Tefera *et al.* (2014) strong financial base enables farmers with high income to adopt new dairy technologies earlier than their low income counterparts. Also, Ingabire *et al.* (2018) stated that small dairy farmers with higher income have the capacity to procure and ultimately adopt AI technology earlier than those with lower income status.

The cost associated with AI technology is a critical factor influencing its adoption among farmers. High costs associated with AI administration may hinder the uptake of this technology or may make the rate of adoption to be lower. Low-income smallholder dairy farmers who cannot afford to pay the higher cost may opt for bull service. Price of semen, labor, and equipment form an important aspect of artificial insemination which may determine the final cost. Temba (2011) notes that smallholder farmers have not been able to

use AI due to costs of equipment, liquid nitrogen and semen. The cost of technology is a major constraint to technology adoption (Bisanda and Mwangi, 1996). Kinyangi (2014) established that the cost of technology was a very strong factor affecting adoption of technology among small holder farmers. Similarly, Kipkemei (2017) also stated the cost of AI will likely increase the chances of adoption of a breeding technology. Moreover, a study by Mwanga *et al.* (2019) established that cost of AI services reduced the probability of the use of AI as a breeding option. Further, Omondi *et al.* (2017) reported that price of AI negatively influenced farmers preference for use of AI implying that farmers were more likely to choose an AI offered at a lower cost.

Natural mating through bull service remains prevalent among many smallholder farmers in rural areas due to its perceived affordability, availability, and simplicity. The difference between cost of AI technology and cost of bull service remains a determinant for the uptake of AI technology in rural areas. The lower cost associated with bull service encourages most rural dairy farmers to use it, neglecting AI technology which offers genetic improvement benefits but is expensive. According Valergakis *et al.* (2007) one of the arguments for using natural service is the higher perceived AI costs compared with those of keeping herd bulls and additional costs resulting from extended calving intervals because of poor heat detection and conception rates when using AI. Mwanga *et al.* (2019) documents that the use of bulls ensures that animals on heat are readily served when in estrus as opposed to AI services which may delay because a service provider is not available, or heat is detected late. Moreover, study by Temesgen *et al.* (2021) reported that most farmers surveyed depended on natural mating because of lack of awareness, unfitness of the animal for AI breeding, long distances, lack of capital, and lack of feed. Further, study by Kitilit *et al.* (2014) reported that availability of cheap bulls from neighbours or their own hindered farmers from adopting AI technology. Moreover, Omondi *et al.* (2017) notes that high

usage of natural mating in smallholder dairy farms in Kenya has been attributed to high availability and affordability of AI. However, natural mating poses a higher risk of sexually transmitted infections, leading to additional veterinary costs. Moreover, reliance on bull service may result in slower genetic process and potential inbreeding issues.

2.2.3 Technical Factors and AI Technology Adoption

One of the primary measures of AI reliability is the conception rate, which refers to the percentage of inseminated animals that become pregnant. High conception rates enhance the perceived reliability of AI, leading to greater adoption. According to Galina *et al.* (2016), low conception rates deter farmers from adopting AI due to the associated economic risks and uncertainties. Tebug *et al.* (2014) found that higher success rates in AI correlate with increased farmer confidence, encouraging wider adoption. Reliable AI is essential for achieving genetic improvement goals. When AI reliably results in high-quality progeny, farmers are more likely to invest in and adopt this technology. Mekonnen *et al.* (2010) highlighted that the promise of genetic gains through reliable AI leads to better productivity and profitability, making it an attractive option for farmers. Similarly, Howley *et al.* (2012) noted that economic benefits derived from reliable AI practices are a significant motivator for adoption. The cost-effectiveness of AI is closely linked to its reliability. When AI procedures are consistently successful, the costs associated with repeat services and veterinary interventions decrease, making AI a more economically viable option. Tey and Brindal (2012) emphasized that the efficiency and cost effectiveness of reliable AI are crucial for its adoption, especially in resource-limited settings.

Heat detection is critical for any successful breeding programme (Perry, 2004). Accurate estrus detection is essential for the timing of AI, which directly influences conception rates and overall herd fertility. Ahisibwe (2019) documents that inaccurate heat detection usually

results in repeat breeding and long calving intervals thus expected losses in terms of milk production. Generally, the signs that may indicate that a dairy animal is on heat may include nervousness, roughed up tail head, swollen vulva, and bloody mucous from the vagina (Perry, 2004; Ahisibwe, 2019) Studies have shown that missed or misidentified estrus periods lead to decreased AI efficiency and higher reproductive costs (Dransfield *et al.,* 1998). According to Roelofs *et al.* (2005), the accuracy of heat detection significantly affects the success of AI programs, with detection rates often ranging from 50% to 70% under typical farm conditions. A study by Bhujel *et al.* (2023) documents farmer not observing heat as a factor limiting AI technology success. The ability of workers to accurately detect estrus has a direct impact on the adoption of AI. Farms with higher estrus detection accuracy tend to have higher AI adoption rates, as the perceived and actual success of the AI program is greater.

The type of semen used in AI significantly influences its adoption among farmers, with factors such as cost, efficacy, and access to technology, farmer preferences, and environmental considerations playing critical roles. While conventional semen remains widely used due to its lower cost and higher conception rates, sexed semen offers advantages in strategic breeding programs aimed at specific production goals. Understanding these dynamics is essential for developing policies and support systems that encourage the adoption of AI technologies tailored to the needs and constraints of different farming communities. Studies have shown that farmers are more likely to adopt AI with conventional semen due to its lower cost and established efficacy (De Vries *et al.,* 2008). However, sexed semen has gained traction in the dairy sector because it allows farmers to produce more female calves, which are preferred for milk production (Crowe *et al.,* 2021). The cost of semen is a crucial factor influencing AI adoption. Sexed semen is more expensive due to the additional processing required to sort the sperm. This higher cost can

be a barrier to adoption, particularly for small-scale or resource-limited farmers. A study by Omondi *et al.* (2017) reported farmers' preference for sexed semen over unsexed semen, imported or local.

Adequate nutrition is essential for maintaining the health and fertility of breeding animals. Supplement feeds, which provide essential nutrients that may be lacking in the base diet, are crucial for enhancing reproductive performance. Poor nutrition, on the other hand, can lead to low conception rates and reproductive failures, which are significant barriers to AI adoption. Supplement feeds can improve the overall body condition of livestock, which is a critical factor for successful AI. Animals in good condition are more likely to exhibit regular estrous cycles and respond positively to hormonal treatments used in synchronization protocols for AI (Perry, 2004). The improved body condition resulting from high-quality supplemental feeds can thus increase the likelihood of successful insemination and conception. The cost of supplement feeds is a critical economic factor influencing AI adoption. While supplement feeds can improve reproductive outcomes, their cost can be prohibitive for some farmers, particularly in developing countries where financial resources are limited (Barrett *et al.,* 2010). However, the long-term benefits of improved productivity and genetic gains often outweigh the initial investment in supplemental feeds, making them a worthwhile expenditure for farmers committed to improving their herds through AI. The accessibility of supplement feeds is another determinant of AI adoption. In regions where these feeds are readily available and affordable, farmers are more likely to adopt AI technologies. Conversely, in areas with limited access to high-quality feeds, farmers may face challenges in maintaining the nutritional status of their livestock, thereby reducing the effectiveness and attractiveness of AI (García *et al.,* 2012). A study by Gebre *et al.* (2022) reported that supplementation of

concentrated feeds had a positive influence on the adoption and intensity of AI technology. Similarly, Tefera (2013) established that feeding concentrates has positive relationship with adoption of AI technology. The author further notes that adopting AI technology to get improved dairy breed and the practice of feeding concentrates together provides synergistic benefits as crossbred cows have larger responses to supplementary feeding.

2.2.4 Institutional Factors and AI Technology Adoption

Extension can be defined as assistance to farmers to enable them identify and analyze their production problems and become aware of opportunities for improvement by changing their outlook towards their difficulties (Msuya, 1998). Regular contact with extension agents enable small dairy farmers to access information about new dairy technologies and ultimately, use them for enhancing productivity and ensuring food security at the household levels (Namwata *et al.,* 2010; Ingabire *et al.,* 2018). According to Temba (2011) extension services positively influenced farmers decision to adopt A.I technology. Abot (2020) also found out that extension services had a positive influence on AI adoption because extension agents act as a link between researchers and farmers, hence reduce the transaction cost associated with technology adoption. Abraha *et al.* (2020) notes that frequency of contacts with extension agents enabled farmers to gain technical advice about the preconditions needed for improved breeding method practice which helped in the adoption of AI. Extension services are measured by the number of visits per month by the extension agent to a farmer. Farmers who had more extension contacts were more likely to access information on the benefits and availability of AI services and even be served by the best inseminators (Temba, 2011). Further, study by Mugisha *et al.* (2014) reported that the demand for extension was high because improved dairy breeds require more extension knowledge and farming skills.

Number of trainings attended by a farmer on livestock production may contribute to adoption of agricultural technologies like AI. Those who attend trainings acquire new skills and knowledge hence increases chances of uptake. Training programs provide farmers with essential knowledge about AI procedures, including handling semen, estrus detection, and proper insemination techniques. This knowledge empowers farmers to effectively implement AI on their farms. Hands-on training sessions allow farmers to gain practical skills in AI implementation. These skills are critical for achieving successful inseminations and maximizing reproductive outcomes among livestock. A study by Dumara and Zenbaba (2020) established that attendance in training had a positive and significant effect on the adoption and intensity of adoption of malt barley technology in Ethiopia. They emphasize that training is one of the means through which farmers get information or knowledge about new technology. Kinyangi (2014) found number of trainings to have a positive influence on adoption of agricultural technology but with low degree of adoption. The low adoption was attributed to the fact that extension workers continued to disseminate the same messages repeatedly to the same audience and the information given was obsolete and outdated. Further, farmers stated that extension workers tend to focus on the well resourced, wealthier farmers leaving poor farmers. Contrary, Mwanga *et al.* (2018) revealed that few farmers attended trainings in sub-Saharan countries. Training programs designed to educate farmers on AI techniques and best practices have been shown to significantly influence adoption rates.

Government support services are crucial for promoting the adoption of AI in agriculture, thereby integrating it into sustainable practices and boosting livestock productivity. Initiatives such as subsidies and financial assistance programs reduce the initial costs of AI technology, making it more accessible to farmers. Investments in veterinary infrastructure, including training centers and semen storage facilities, enhance the delivery of AI services

in rural areas (Mekonnen *et al.,* 2010). Government-led training programs educate farmers about AI benefits and techniques, closing knowledge gaps and increasing adoption rates (Ndambi *et al.,* 2019). Moreover, supportive policies and regulations foster an environment that ensures quality, safety, and ethical standards in AI application. Support services such as good transport for the inseminators and storage facilities for semen are very important. Good transport ensures the availability of inseminator at the required areas. Mpofu (2002) when studying the importance of breeding infrastructure and support services indicated that livestock identification, performance recording and evaluation programs, research, training and extension programs, farmers' associations, and supply of replacement animals were important for the successes of AI.

The availability of the AI technician is an important factor when it comes to adoption. If he/she is available at the required time chances of using this technology are enhanced, and chances of using an alternative methods are high when the technician is not available. Farmers are more likely to adopt AI when inseminators are locally accessible, reducing logistical barriers and costs associated with travel and waiting times. Karawita (2008) noted that there will be no AI service in a certain locality if an inseminator is not available. Moreover lack of mobility and large area of operation is the main constraint for the inseminators. Bhujel *et al.* (2023) cites logistics challenges to be associated with low AI coverage for the case of farmers in scattered and far flung with human settlements away from AI centres. There must be a means to ensure the inseminator is available to the farmer at the required time. Improvement of infrastructure and provision of transport means are necessary. Schuttle and Perera (2004), recommended motor vehicles and light motor bikes as possible means for inseminators to reach farmers.

2.4 Theoretical Framework

The study is based on the Innovation Diffusion Theory by Rogers (1995). According to the theory, innovations are not adopted by all individuals in a social system at the same time. According to Rogers and Shoemaker (1971), innovativeness is considered a relative concept and is categorized into five distinct groups based on their characteristics: innovators (2.5%), early adopters (13%), early majority (34%), late majority (34%), and laggards (16%). The early adopters are usually respected by their peers and have a reputation for successful and discrete use of new ideas (Rogers & Shoemaker, 1971). The innovation decision process, which aims to reduce uncertainty about an innovation, outlines how individuals or decision-making units adopt or reject an innovation. This process consists of five steps; knowledge, persuasion, decision, implementation, and confirmation that do not necessarily occur in a fixed sequence. Moreover, Rogers and Shoemaker (1971) documents that extension services or institutions passing over the knowledge to the farmers to help in decision making on technology use, play a role in adoption but need to know the categorization too of characters.

According to Rogers (1995), diffusions are special type of communications concerned with the spread of messages that are perceived as new ideas. Though interacting factors influences diffusions of innovations. Diffusion is defined as the process by which an innovation is adopted and gains acceptance by members of a certain community. According to Rogers (1995) four major factors that influence diffusion of innovation includes the innovation itself, how information about the innovation is communicated, time, and the nature of the social system into which the innovation is being introduces.

Innovations is an idea, practice, or object that is perceived as new by an individual or other unit of adoption (Rogers, 1995). According to Hahn and Schoch (1997) the diffusions of

innovations suggest that acceptance or adoption is significantly influenced by innovations characteristics and adoptions perceptions. Innovations diffusions theory proposes five attributes of innovations that shape adoption or rejection relative advantages, compatibility, complexity, trialability, and observability. The rate at which an innovation is adopted or fails, hinges on the attributes of the innovations and the potentials adopters' opinions.

Another element within Rogers' (1995) innovation diffusion theory is the communication channel, the means by which messages travel from one individual to another. In fact, diffusion itself is a form of communication wherein the spread of a message concerns something new. Hangerstrand (1967) argues that the spread of innovation is primarily the outcome of a learning or communication process. Indeed, communication will create the awareness of an innovation to the potential adopter, helping him/her to form a kind of attitude that will eventually determine the decision to adopt or reject. According to Rogers (1995) mass media channels are often the most rapid and efficient means to inform an audience of potential adopters about the existence of an innovation. Personal communication (face-to-face) is also important and tends to be more effective in transmitting information and changing attitudes (Howard, 1969; Coleman *et al.,* 1957). The channel being the extension services, artificial inseminator plays a role in A.I adoption.

Time, the third general area Rogers (1995) suggests, plays a critical role in any technological progress because it defines both the pace at which progress occurs and the positions individuals occupy amid the evolution of such progress. Time dimensions specifically refers to the length of time by which innovation is fully convincing for potential adopters to decide for the adoption or rejection of innovation (Dibra, 2015). According to Rogers (1995), individuals who are predisposed to being innovative will adopt an innovation earlier than those who are less predisposed. Rogers's (1995, 2003),

views the process of innovation decision making as a linear five-stage mental process through which an individual (or some other decision-making unit) goes, namely, knowledge, persuasion, decision, implementation, and confirmation.

Finally, the social system element of Rogers's innovation diffusion theory is a means through which participants, for our case farmers create and share information with each other through communication channels in order to reach a mutual understanding on innovation. According to Rogers (2003) a social system as a set of interrelated units engaged in joint problem solving to accomplish a common goal. Since diffusion of innovations takes place in the social system, it is influenced by the social structure of the social system. For Rogers (2003), structure is the patterned arrangements of the units in a system. The author further claimed that the nature of the social system affects individuals' innovativeness, which is the main criterion for categorizing adopters.

2.5 Empirical Literature

A number of studies have been carried to assess the factors associated with the adoption of artificial insemination globally. For instance, Gebre *et al.* (2022) assessed the factors affecting adoption decision and the intensity of AI in Eastern Tigray national regional state of Ethiopia using primary data of 204 farmers. Results revealed that households' level of literacy, milk yield, income, training, access to extension service, mobile ownership, supplementation of concentrated feed and hybrid cattle ownership were found to have a positive and statistically significant relationship with adoption and intensity of AI technology, whereas distance to farmer training office had shown a negative relationship. They recommend that the extension system should give more emphasis to the capacity building which is pivotal for introducing, adoption, and scaling out of best practices of dairy technologies, and the participation of the private sector in AI technology.

Herana and Kumari (2017) investigated factors affecting adoption and intensity of artificial insemination (AI) technology among dairy in Ethiopia. The results showed that land holdings, information accessibility, artificial insemination training and support had a positive and herd size had a negative statistical significant effect on adoption and intensity of adoption. The study emphasized the need to strengthen extension and research activities in order to spread the uptake of AI technology which will help improve the yield potential of small dairy farm holders.

Akin and Kara (2019) utilized data from 546 breeders to assess determining on the farmers' decision to use AI to improve milk and beef yields of low-yielding local cattle breed in Turkey. The results revealed a significant relationship between membership status and AI technology. Moreover, government incentives, number of cross- and purebred cattle, and information source had a positive effect on the willing of the farmers to employ AI, while breeder age, distance from the closest city centre, farm family size, and share of crop revenue in the total revenue had a negative effect on the adoption of AI. In order to achieve the successful results, more sustainable, robust, and long-term policies should developed and implemented to address the existing problems impeding the success of AI.

Kosgei *et al.* (2020) assessed the factors affecting adoption of dairy cattle milk production technologies by smallholder dairy farmers in Mosop sub county, Nandi County using primary data from a sample size of 199. Results revealed that the education level of the household head had a positive and significance marginal effect on the adoption of milk equipment technologies.

The relevance of dairy cattle technology was positive and had a positive effect on the adoption of AI. The results further revealed that land size had a positive and significant marginal effect on the adoption of AI. The marginal effects result on milk chilling plants

revealed that there was a positive relationship with the adoption of dairy cattle milk production technologies The study recommends that the county government should strengthen and revamp the extension service in order to aid dissemination of dairy cattle milk production technologies and continued use of the same by the farmers, and that policies and initiatives that would go towards empowering farmers economically.

Okello *et al.* (2021) examined the determinants and intensity of use of dairy technologies among smallholder farmers in Kenya using survey data from 682 households. The author examined six dairy technologies: artificial insemination, deworming, vaccination, curative treatment, improved feeds, and pregnancy diagnosis. The results revealed that education of the household head, number of cows owned, milk output, access to contract distance to veterinary clinics, remittances, membership to cooperatives, and access to support service determined the utilization of AI. The study emphasized the need to empower smallholder farmers, and capacity building programs in business planning and animal breeding to enhance the uptake of these important technologies.

In another study, Sapkota *et al.* (2016) investigated the adoption of artificial insemination technology in dairy animals and its impact on milk production in Nepal. The study focused on cows and buffaloes. The results revealed a higher adoption rate in cows than buffaloes. AI was less successful in buffaloes due to difficulties in heat detection and thus, the farmers were compelled to sell buffaloes for meat due to repeated failures of AI. Further, results established a positive relation between AI practice and milk yield. The authors emphasize the need for increased capacity of public and private sectors in transferring AI technology to the farmers so as to achieve higher level of success in AI services.

Abot (2020) analyzed factors influencing adoption of AI by smallholder livestock farmers in dry land production systems of Kenya using primary data from 398 randomly selected

smallholder livestock farmers and employing the double hurdle model. The study revealed low adoption of AI among the pastoralists in the ASALs. The results indicated that access to extension services, age, education level, contract farming, and cattle farm size had positive influence, while household size, off-farm employment, access to information, group membership and distance to market had negative influence on AI adoption. The author also reported 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. The study recommended the application of information communication (ICT) to promote extension service, training and dissemination workshops, promotion of pastoral education, and expansion of AI centres.

In another study in Ethiopia, Abraha *et al.* (2020) assessed adoption of artificial insemination service for cattle crossbreeding by smallholder farmers using a sample of 155 respondents. The findings showed that farmers' adoption of AI was influenced by access to credit facilities and mobile phone, social participation, formal training, frequency of extension contact, knowledge about AI practice and perception of AI profit positively and participating in off-farm activities negatively. The authors suggested the need to improve the effectiveness of extension service through strengthening the training, frequent home visit, making credit service accessible, and education farmers regarding the knowledge and importance of AI technology for its effective dissemination.

Ahisibwe (2019) determined farmer factors affecting the use and performance of AI among dairy farms in Western Uganda. The study mainly focused on the area extension workers, AI technicians and the dairy farmers. The results revealed a low use of AI (26%), and it was associated with age of a farmer, availability and use of extension services, and cattle

ownership. Moreover, a great number of farmers admitted knowing that borrowed bulls may bring in diseases to the farm but continued with the practice. The author also noted that AI technicians lacked current techniques, as they had never been retrained.

In another study, Bayan (2018) in India analyzed socio-economic factors to determine whether they have an influence on the extent of AI adoption technology in the crossbreeding systems at the farm household level in Assam. Factors that were analyzed included education of the household head, accessing support from the government dairy development programme, number of since farmers knew about AI, proportion of net dairy income, distance to the nearest market and risk perception of the farmers on AI. The author established a positive and significant influence of the education of the household head, accessing support from government dairy development programme, number of years since farmers first knew about AI and proportion of net dairy income on the extent of AI adoption. Other factors such as distance to nearest market and risk perception of the farmers on AI had negative influence on extend of AI adoption.

In Rwanda, Ingabire *et al.* (2018) assessed factors affecting adoption of AI technology by small dairy farmers using primary data. The study depicted that age, gender, education status, extension services, household income, distance from AI centers and access to credit were statistically significant implying their positive contributions to the adoption of AI technology among small dairy farmers. Contrary, farming experience, land size and marketing services were insignificant and hence a negative influence on adoption of AI technology in the study area. The study recommended that the responsible authorities should allocate more resources for capacity building in productive areas.

In another study, Ozsayin (2020) analyzed factors affecting the use of artificial insemination of farmers in dairy farming in Turkey using primary data from 252 dairy

cattle farms. The results revealed that the educational level of the farmers, dairy farming experience, the number of dairy cattle, livestock diseases, off-farm income, artificial insemination support and access to veterinary services variables had a positive effect on farmers' use of artificial insemination; whereas age and household size variables had a negative impact. As a result, the use of artificial insemination in dairy farm can be increased with farmers who are open to innovations regarding livestock activity and knowledgeable about artificial insemination.

2.6 Conceptual Framework

According to Mugenda and Mugenda (2003), a conceptual framework represents the conceptualization of relationships between variables in a study and is illustrated graphically or diagrammatically. It is considered essential as it helps the researcher quickly understand the established relationships. A.I technology adoption and intensity are the dependent variables while Social factors, Economic factors, Technical factors and institutional factors are the independent variables (see figure 2.1).

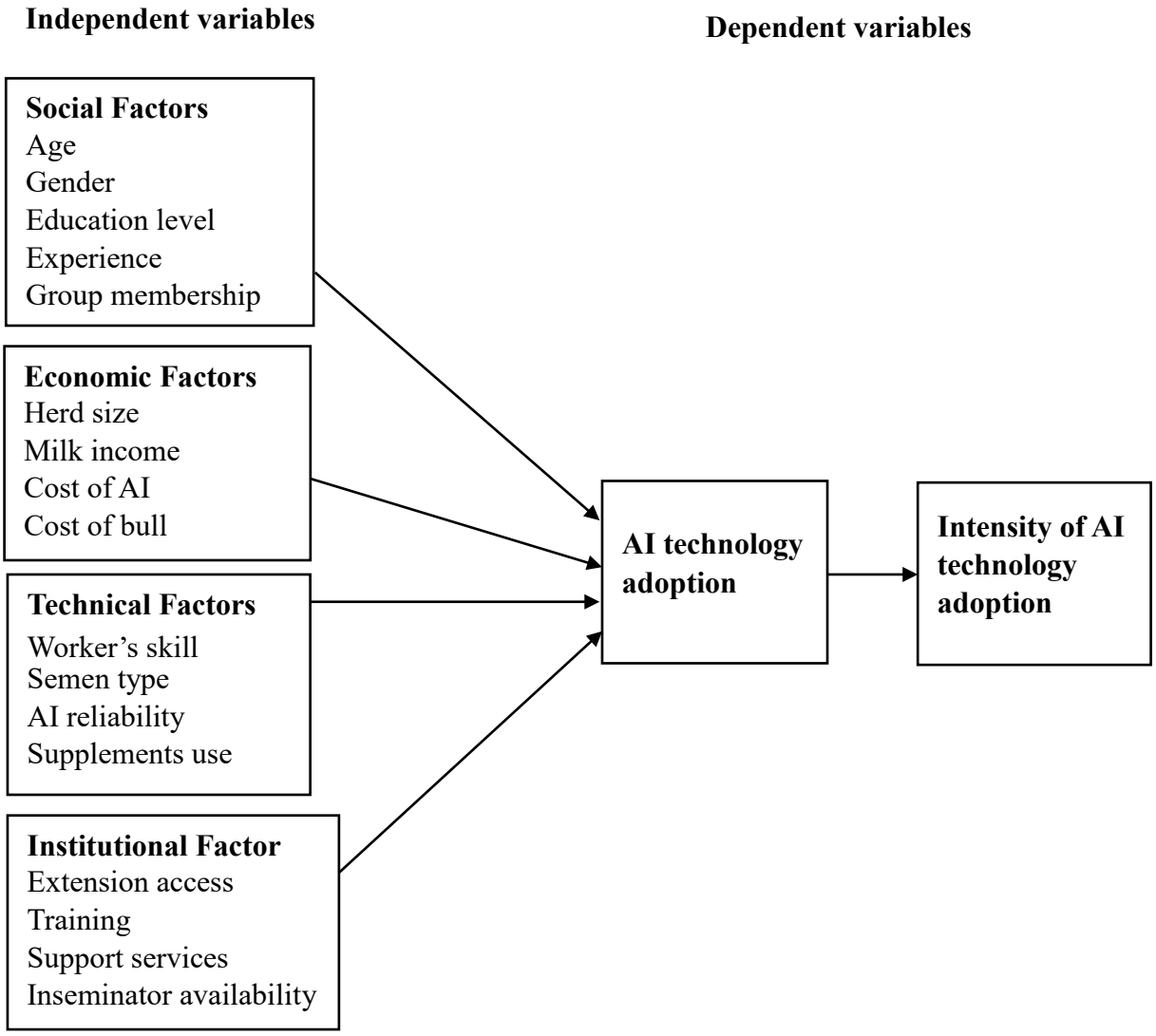

Figure 2. 1 Conceptual Framework Source: Author, 2024

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Study Area

The study area was Alego-Usonga sub-county that covers an area of 599 square kilometres within Siaya county which is 2,530 square kilometres with a population of 224,363 people and

Siaya county 993,183 (KNBS, 2019). The population is made of mixed farmers comprising 3,512 households who account for 26% of the milk produced and 81% of marketed milk and are known to hire labour for dairy management activities. The smallholder dairy farmers keep 1-5 cows on an average of 0.5 to 3 acres. The grade cows produce 3.4 litres per cow per day and zebu cows 2.4 litres per cow per day (ASDSP, 2014).

Siaya has bimodal rainfall seasons distributed within the Northern parts of Ugunja, Gem and Ugenya receiving the highest amount between 1600-2000mm and rainfall gradually reducing to Southern parts of Bondo and Rarieda which receive the lowest amounts between 800-1200mm annually; temperature ranges from 15 to 32 degree Celsius with an annual average of 28degrees

Celsius (Directorate of Livestock Production and Veterinary, 2019).

3.2 Research Design

The study was guided by a Cross-sectional study design. The design allows data to be collected at a single point in time and is used for descriptive study as well as determining relationships between and among variables (Byerlee and Heisey, 1992). It allows direct information seeking regarding the factors affecting adoption of A.I amongst smallholder

dairy farmers in Alego– Usonga Sub County. This design has greater degree of accuracy and precision in social science study than other designs (Casley and Kumar, 1998).

3.3 Study Population

The target population was Alego-Usonga smallholder farmers. The target population comprised 22965 smallholder dairy farmers.

3.4 Data Types and Sources

Both primary data and secondary data was obtained from the respondents. Primary data was obtained from the farmers directly and other stake holders through interviews, Annual reports from Siaya County, directorate of veterinary and livestock production provided the secondary data, County Integrated Development Plan (CIDP) Siaya county, Economic survey 2020, KDB

reports.

3.5 Sample Size Determination and Sampling Procedure

3.5.1 Sample Size Determination

Determination of sample size was through the use of the formula by Kothari (2004), hence 378 farmers out of the finite number of 22,965 small-scale dairy farmers would be a representative in the study. The formula for sample size determination:

$$n = \frac{Z^2.p.q.N}{e^2(N-1)+Z^2p.q} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (3.1)$$

Where: N= population Size, n = the desired sample size z – Standard normal deviate at 0.05 significance level p – the proportion in the target population estimate to have a characteristic being measured (p is 0.5).

q=1-p

e = level of statistical significance

z - statistic at 95% confidence level is 1.96.

The level of significance being 0.05 therefore, the sample size, n,

$$n = \frac{(1.96)^2 \times (0.5)(0.5)(22965)}{0.0025(22964)+3.8416X0.25}$$

$$n = \frac{22055.5860}{58.3704}$$

$$=377.85565772$$

$$=378$$

3.5.2 Sampling Procedure

A multistage sampling technique was employed in this study to ensure a systematic, efficient, and representative selection of smallholder dairy farmers in Alego-Usonga sub-county. In the first stage, Alego-Usonga was purposively selected as the study area based on its significant population of smallholder dairy farmers, making it relevant to the study objectives. In the second stage, the six administrative wards: North Alego, Central Alego, Township, South East Alego, South West Alego, and West were selected to ensure comprehensive geographical coverage, resulting in a more balanced and representative sample. In the third stage, proportionate sampling was used to obtain the representative sample for every ward in accordance to their numbers. In the final stage, systematic sampling was used to get every ***i***th respondent from the list of farmers obtained from the artificial insemination service provider. Using proportionate sampling the sample size for each ward was as follows:

Table 3.1: Sample Proportions

Ward	Target Population	Proportion (%)	Proportionate size sample	Target Sample
North Alego	9860	43%	0.43	162
Central Alego	7125	31%	0.31	117
Township	2526	11%	0.11	42
South East Alego	1380	6%	0.06	23
South West	923	4%	0.04	15
West	1151	5%	0.05	19
Total	**22965**			**378**

Source: Author's Computation (2025)

3.6 Data Collection Method, Procedure and Instruments

Structured questionnaires were administered by enumerators to collect data from smallholder dairy farmers. A questionnaire is a data collection tool consisting of a set of questions designed for research purposes. This study utilized both open-ended and close-ended questions to gather quantitative and qualitative data for each research objective.

3.7 Data Processing and Analysis

Both descriptive and inferential statistics were applied to the data to identify factors influencing the adoption of AI technology and intensity of use in Alego-Usonga. After data collection, cleaning was done using Microsoft Excel software. STATA software version 15 was utilized to analyze quantitative data collected from the household survey.

3.7.1 Descriptive Statistics

Descriptive statistics provide detailed analysis of selected households, summarizing key characteristics such as demographics, technical factors, institutional factors, and the

adoption of artificial insemination. In this case, cross tabulation, frequency tables and general statistics such as means, standard deviations of certain variables were determined.

3.7.2 Inferential Statistics

Inferential statistics aid in drawing conclusion and making predictions about a population based on sample results. Regression analysis was used to establish the existence of significant relationships among variables between farmer characteristics and their willingness to adopt artificial insemination services in the area of study. Multicollinearity check was performed by analyzing correlations between independent variables and any Variance Inflation Factor (VIF) values equal or greater than 5 were considered highly correlated. The t-test statistics was used to determine if there is a significant difference between adopters and non-adopters of A.I services.

All tests of significance in this study were computed at $\alpha = 0.05$.

3.7.3 Empirical Model Specification

The Cragg (1971) Double Hurdle model was employed in this study to analyze factors influencing the adoption and the intensity of use AI technology in Alego Usonga Sub County.

The model is a less restrictive variant of the Heckman and is best suited for samples drawn through random probabilistic sampling procedures. The model is a generalization of the Tobit, where two separate stochastic processes determine the participation and quantity decisions. According to Cragg (1971), adoption is a process involving two stages/tiers; the first is whether or not to adopt the technology, and second is to what extent to adopt. The model assumes that the decision not to adopt is a deliberate choice, thus the zeros from non-participants are considered as corners solution in the utility maximizing model. The model further curbs bias in the continuous second tier dependent variable by linking a value

to the piled up data, thus maintaining all the data within the sample. Moreover, the model is flexible, assuming that there are no restrictions regarding the components of independent variables in each estimation stage. The model requires a joint application of the probit and truncated regression models, sequentially or simultaneously. The probit model equation that was used in the study is given by

$$Y_i^* = \beta_i X_i + \varepsilon_i$$

$$Y_i = \begin{cases} 1 \text{ if } Y_i^* > 0 \\ 0 \text{ if } Y_i^* \leq 0 \end{cases} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.2)$$

Where subscript $\boldsymbol{i}$ is the $\boldsymbol{i}$th household, $\boldsymbol{Y_i^*}$ is the latent discrete adoption choice variable, $\boldsymbol{Y_i}$ is the observed adoption variable which takes a value of 1 if the farmer adopted AI technology and 0 otherwise, $\boldsymbol{X_i}$ is Kx1 vector of factors that influence AI technology adoption, $\boldsymbol{\beta_i}$ is a Kx1 vector of parameters to be estimated, $\boldsymbol{\varepsilon_i}$ is the error term.

In the second hurdle, the truncated regression model was employed to determine factors that influence the intensity of AI technology adoption among farmers who adopted the technology.

The truncated regression is given by

$$I_i^* = \alpha_i X_i + \mu_i \qquad \mu_i \sim N(0, \delta^2)$$

$$I_i = \begin{cases} I_i^* \text{ if } I_i^* > 0 \text{ and } Y_i = 1 \\ 0 \text{ otherwise} \end{cases} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.3)$$

Where $\boldsymbol{I_i}$ is the intensity of AI technology adoption, and depends on $\boldsymbol{I_i^*}$ is the latent variable being greater than zero on the condition that a decision is made to adopt AI technology. $\boldsymbol{\alpha_i}$ is a vector of parameters to be estimated for the intensity of adoption, $\boldsymbol{X_i}$ is a vector of factors that influence the intensity of use of AI technology, $\boldsymbol{\mu_i}$ is the error term which has a normal distribution. The double-hurdle regression equation is specified as follows:

$$Y_i \text{ or } I_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3, \ldots, \beta_n X_n + \varepsilon_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.4)$$

where Y_i is the AI adoption which takes a value of 1 for adopters and 0 otherwise, I_i is intensity of use of AI measured by the number of times a farmer used the technology, β_i is a vector of parameters to be estimated, X_i is vector of the explanatory variables, and ε_i is the error term.

The independent variables that were used in the double hurdle model analysis together with their definitions and hypothesized signs are presented in **Table 3.2**

Table 3.2: Variable Measurements and Apriori Expectations

Variable	**Measurement**	**Expected sign**
Dependent		
Adoption of AI	1 if adopted and 0 otherwise	
Intensity of AI adoption	Number of times used AI/cow	
Independent		
Age	In years	+/-
Gender	1 = Male, 0 = Female	+/-
Education level	1=non-formal 2=primary 3=secondary 4=college/university (tertiary)	+
Experience	In years	+/-
Group membership	Active group member 1 = yes, 0 = no	+
Herd size	In numbers	+
Milk income	Income in Ksh	+
AI cost	Cost in Ksh.	-
Cost of bull	Cost in Ksh	-
Worker's skill on heat detection	1= poor 2 = good 3 = very good 4 = excellent	+/-
Semen type	1 = Sexed 2 = Normal 3 = imported 4 = Don't know	+/-
AI reliability	If it is reliable 1 = yes, 0 = no	+
Supplements use	If they give supplement feeds 1 = yes, 0 = no	+

Extension access	Access and availability of extension service 1 = yes, 0 = no	+
Training	Attended any training	+
	1 = yes, 0=no	
Support services	Whether support services are available 1 = yes, 0 = no	+
Inseminator availability	Is the inseminator available? 1 = yes, 0 = no	+

Source: Author's Computation (2025)

3.8 Ethical Considerations

Permission to conduct the research in the study area was obtained from the National Commission for Science, Technology, and Innovation (NACOSTI). The study followed established ethical guidelines to guarantee that the rights of participants were safeguarded throughout the research process. Participants were informed of the objective of the study, and no one was coerced to take part in the study. Additionally, all collected data was used solely for the purpose of this study and handled with the highest level of confidentiality to protect the identities and privacy of the participants.

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 Response Rate

A sample size of 378 farmers was selected to take part in the study. The researcher gave out 378 questionnaires for data collection. However, 340 questionnaires were returned of which 332 questionnaires were properly filled. This presented 97.6% of the total successful response rate.

Out of the total sample size of 378, the total successful rate represent 87.8%. According to Mugenda and Mugenda (2009) a response rate of 50% is considered adequate, 60% is good, and 70% and above is very good for analysis. This means that a 97.6% response rate was proper for data analysis.

4.2 Descriptive Analysis Results of the Small Scale Dairy Farmers

This section presents the descriptive results of key variables examined that included; social, economic, technical, and institutional factors. Table 4.1 of results on age and AI technology adoption shows that 3.01% of the small scale dairy farmers were aged between 20 – 29 years, 8.73% were aged between 30 – 39 years, 40.96% were aged between 40 – 49 years, and 47.29% were above 50 years of age. These findings show that majority of small scale dairy farmers were aged 40 years and above, with nearly half of the farmers being over 50 years old. This suggests that most of the farmers are still in their active production stage.

Table 4.1: Age and AI Technology Adoption

Age	Adoption					
	Non-Adopters		Adopters		Total	
	N	%	N	%	N	%
20 – 29 Years	5	4.95	5	2.16	10	3.01
30 – 39 years	14	13.86	15	6.49	29	8.73
40 – 49 years	41	40.59	95	41.13	136	40.96
Above 50 years	41	40.59	116	50.22	157	47.29
Total	101	100	231	100	332	100

Source: Survey Data (2025)

Table 4.2 of results on gender of the respondent shows that 54.22% of small scale dairy farmers were female, while 45.78% were male farmers. Further, 55.45% of the female and 44.55% of the male farmers were non-adopters, while 53.68% of the female and 46.32% of the male were adopters of AI technology. These findings suggest that while both genders participate in AI technology adoption, the distribution is relatively balanced, with females being slightly more represented in both adoption and non-adoption categories.

Table 4.2: Gender and AI Technology Adoption

Gender of respondent	AI Adoption					
	Non adopters		Adopters		Total	
	N	%	N	%	N	%
Female	56	55.45	124	54.22	180	54.22
Male	45	44.55	107	45.78	152	45.78
Total	**101**	**100**	**231**	**100**	**332**	**100**

Source: Survey Data (2025)

Table 4.3 shows results on education level of small scale dairy farmers and AI technology adoption in the study area. The findings indicate that 25% of the farmers did not have any kind of formal education, 38.86% had primary level education, 18.67% had secondary level

education, and 17.47% reached college and any institution of higher learning. These findings show that most of small scale dairy farmers had a basic education, with a smaller proportion having secondary or higher education. The relatively lower percentage of farmers with advanced education could influence the adoption of AI technology, as higher education levels are often associated with better access to information and improved decision-making.

Table 4.3: Education Level and AI Technology Adoption

Education level	AI Adoption					
	Non-Adopters		Adopters		Total	
	N	%	N	%	N	%
Non formal	24	23.76	59	25.54	83	25
Primary	46	45.54	83	35.93	129	38.86
Secondary	17	16.83	45	19.48	62	18.67
College and Above	14	13.86	44	19.05	58	17.47
Total	**101**	**100**	**231**	**100**	**332**	**100**

Source: Survey Data (2025)

Table 4.4 of results on dairy farming experience and AI technology adoption in the study area shows that 3.31% of the small scale dairy farmers had less than 1 year of experience, 28.01% had 1 – 5 years of experience, and 68.67% had more than 5 years of dairy farming experience. These results shows that a majority of AI users (68.83%) in the study area had more than 5 years dairy farming experience, implying that farmers were well experienced.

Table 4.4: Experience and AI Technology Adoption

Experience	AI Adoption					
	Non adopters		Adopters		Total	
	N	%	N	%	N	%
Less than 1 year	5	4.95	6	2.6	11	3.31
1 - 5 years	27	26.73	66	28.57	93	28.01
More than 5 years	69	68.32	159	68.83	228	68.67
Total	**101**	**100**	**231**	**100**	**332**	**100**

Source: Survey Data (2025)

Table 4.5 of results on group membership and AI technology adoption in the study area showed that 60.54% of the small scale dairy farmers were not members of any group, while 39.46% were members of various farmer groups. Further, results showed 59.41% of the non-adopters and 61.04% of the adopters were not members of any group, while 40.59% of the non-adopters and 38.96% of the adopter were members of the various groups. These findings suggest that group membership was not a major determinant of AI technology adoption, as both AI adopters and non-adopters had a similar distribution of group participation. However, a slightly higher proportion of non-adopters were group members compared to adopters.

Table 4.5: Group Membership and AI Technology Adoption

Group membership	AI Adoption					
	Non-adopters		Adopters		Total	
	N	%	N	%	N	%
No	60	59.41	141	60.54	201	60.54
Yes	41	40.49	90	39.46	132	39.46
Total	**101**	**100**	**231**	**100**	**332**	**100**

Source: Survey Data (2025)

Table 4.6 of results on the cost of AI and AI technology adoption among small scale dairy farmers in the study area showed that 38.1% of the farmers who adopted the technology paid between Ksh. 1000 – 2000, and 61.9% of the farmers paid above Ksh. 2000. The result showed that the cost of AI technology among small-scale dairy farmers in the study area is relatively high for most adopters, and a limiting factor for some farmers who have not yet adopted the technology. The variation in costs (with 38.1% paying Ksh. 1000-2000 and the majority paying above Ksh. 2000) could indicate differences in service providers, quality of semen, or accessibility of AI services.

Table 4.6: Cost of AI and AI Technology Adoption

	AI Adoption	
	Adopters	
Cost of AI	**N**	**%**
1000 – 2000	88	38.1
Above 2000	143	61.9
Total	**231**	**100**

Source: Survey Data (2025)

Table 4.7 of results on the various responses of small scale dairy farmers with regards to worker's skill on heat detection in the study area showed that 47.19% of the small scale dairy farmers who adopted the technology rated the worker's skill on heat detection to be poor, 49.35% good, 0.87% very good, and 2.6% excellent. These findings suggest that the skill level of worker in heat detection among small-scale dairy farmers in the study area is generally low to moderate. The skill gap in heat detection among workers could be a major constraint in optimizing AI technology among small-scale dairy farmers in the study area.

Table 4.7: Worker's Skill on Heat Detection and AI Technology Adoption

Worker's skill on heat detection	AI Adoption	
	Adopters	
	N	%
Poor	109	47.19
Good	114	49.35
Very good	2	0.87
Excellent	6	2.60
Total	**231**	**100.00**

Source: Survey Data (2025)

Table 4.8 of results on type of semen used by small scale dairy farmers and AI technology adoption in the study area showed that 23.38% of the adopters used sexed semen, 4.33% use normal (local) semen, 1.3% use imported semen, while 71% did not know the type of semen used. These results show that a majority of the small scale dairy farmers in the study area did not know the type of semen they used, implying that most were not involved in AI decision making and semen selection was done by the inseminator.

Table 4.8: Semen Type and AI Technology Adoption

Type of semen used	AI Adoption	
	Adopters	
	N	%
Sexed	54	23.38
Normal	10	4.33
Imported	3	1.30
Don't know	164	71.00
Total	**231**	**100.00**

Source: Survey Data (2025)

Table 4.9 of results on AI reliability and AI technology adoption among small scale dairy farmers in the study area shows that 54.55% of the adopters stated that AI was not reliable, while 45.45% reported that the technology was reliable. The results suggest that there is a divided perception among small-scale dairy farmers regarding the reliability of AI technology, with most of the small scale dairy farmers having concerns about the effectiveness of the technology.

Table 4.9: AI Reliability and AI Technology Adoption

AI reliability	AI Adoption	
	Adopters	
	N	**%**
No	126	54.55
Yes	105	45.45
Total	**231**	**100.00**

Source: Survey Data (2025)

Table 4.10 of results on the supplements use by small scale dairy farmers in the study area showed that 13.55% of the farmers did not give supplements to their cows, while 86.45% gave supplement feeds to their animals. Further, results showed 21.78% of the non-adopters and 9.96% of the adopters did not give supplement feeds to their cows, while 78.22% of the non-adopters and 90.04% of the adopters gave supplement feeds to their cows. These results showed that a majority of the AI users in the study area gave supplements feeds to their animals.

Additionally, the findings suggest that AI technology adopters were more likely to provide supplement feeds to their cows compared to non-adopters. This could indicate that AI

technology adopters are generally more inclined toward improved dairy management practices, which may contribute to better productivity.

Table 4.10: Supplements Use and AI Technology Adoption

Supplements use by farmer	AI adoption					
	Non-adopters		Adopters		Total	
	N	%	N	%	N	%
No	22	21.78	23	9.96	45	13.55
Yes	79	78.22	208	90.04	287	86.45
Total	**101**	**100**	**231**	**100**	**332**	**100**

Source: Survey Data (2025)

Table 4.11 of results on access to extension services and AI technology adoption in the study area showed that 12.95% of the small scale dairy farmers did not access extension services, while 87.05% accessed extension services. Further, results showed that 9.9% of the non-adopters and 14.29% of the adopters did not access extension services, while 90.1% of the non-adopters and 85.71% of the adopters accessed extension services. These findings suggest that access to extension services was generally high among both adopters and non-adopters. However, a slightly higher percentage of non-adopters had access to extension services compared to adopters, indicators that while extension services are important, other factors may also influence the decision to adopt AI technology.

Table 4.11: Extension Access and AI Technology Adoption

Extension services access	AI adoption					
	Non-Adopters		Adopters		Total	
	N	%	N	%	N	%
No	10	9.9	33	14.29	43	12.95
Yes	91	90.1	198	85.71	289	87.05
Total	**101**	**100**	**231**	**100**	**332**	**100**

Source: Survey Data (2025)

Table 4.12 of results on the farmers' response with regards to livestock production training attendance by small scale dairy farmers in the study area showed that 28.01% of the small scale dairy farmers did not attend training on livestock production, while 71.99% attended trainings. Further, 20.79% of non-adopters and 31.17% of the adopters did not attend livestock production training. Additionally, 79.21% of the non-adopters and 68.83% of the adopters attended livestock production training. This shows that majority of the small scale dairy farmers attended livestock production training. However, a higher proportion of the non-adopters attended training compared to adopters. This indicates that while training is important, it does not necessarily translated directly in AI technology adoption, suggesting that factors may also influence adoption decisions.

Table 4.12: Training and AI Technology Adoption

Participation in training	AI adoption					
	Non-Adopters		Adopters		N Total	
	N	%	N	%		%
No	21	20.79	72	31.17	93	28.01
Yes	80	79.21	159	68.83	239	71.99
Total	**101**	**100**	**231**	**100**	**332**	**100**

Source: Survey Data (2025)

Table 4.13 of results on government support and AI technology adoption among small-scale dairy farmers in the study area showed that 93.07% did not receive any form of government support, while 6.93% did receive. Further, 92.21% of the adopters and 95.05% of the non-adopters did not receive any government support. Additionally, 7.79% of the adopters and 4.95% of the non-adopters received some form of government support. The current results suggest that government support for small-scale dairy farmers was generally low, with only a small proportion benefitting from it. While slightly more adopters received government support compared to non-adopters, the overall low levels of assistance indicate that government interventions may not have played a significant role in influencing AI technology adoption.

Table 4.13: Support Services and AI Technology Adoption

Government support services	AI adoption					
	Non-Adopters		Adopters		Total	
	N	%	N	%	N	%
No	96	95.05	213	92.21	309	93.07
Yes	5	4.95	18	7.79	23	6.93
Total	**101**	**100**	**231**	**100**	**332**	**100**

Source: Survey Data (2025)

Table 4.14 of results on the availability of inseminator and AI technology adoption among small scale dairy farmers in the study area showed that 12.99% of the adopters reported that inseminator is not available when called, while 87.01% of the small scale dairy farmers reported that the inseminator is always available. The findings suggest that the availability of the inseminator is generally high among small-scale dairy farmers in the study area.

Table 4.14: Inseminator Availability and AI Technology Adoption

Availability of the inseminator	AI Adoption	
	Adopters	
	N	%
No	30	12.99
Yes	201	87.01
Total	**231**	**100.00**

Source: Survey Data (2025)

Table 4.15 presents the summary results for herd size, daily milk sales, and cost of bull. The results revealed that on average, households in the study area had 3 cows with the lowest being one cow and the highest fourteen cows. Further, the mean daily milk sales was KSh. 455 with the lowest earning KSh. 60 and the highest being KSh. 2,450. Moreover, on average the use of a bull costed KSh. 854 with the lowest cost being KSh. 200 and the highest cost being KSh. 3,000.

Table 4.15: Descriptive Statistics for Continuous Variables

Variable	Observation	Mean	Standard deviation	Min	Max
Herd size	332	3.66	2.08	1	14
Milk sales	332	455.527	267.812	60	2450
Cost of bull	332	854.518	376.292	200	3000

Source: Survey Data (2025)

4.3 Econometric Results for Small-scale Dairy Farmers

This section presents the inferential statistics results of the main variables used to analyze the determinants of adoption and intensity of AI technology in the study area.

4.3.1 Diagnostic Test Results

Table 4.16 presents the Variance Inflation Factor (VIF) results utilized to test for the presence of multicollinearity among the independent variables used in this study. The results revealed that all the variables under study had a VIF below 5, which indicates a low level of correlation, or there is a moderate correlation and therefore, no variable in this study was dropped.

Table 4.16: Variance Inflation Factor

Variable	VIF	1/VIF
Inseminator availability	1.454	0.688
Cost of bull	1.447	0.691
Worker's skill	1.376	0.727
Age	1.305	0.767
Group membership	1.295	0.772
AI cost1	1.291	0.775
Milk sales	1.267	0.789
Herd size	1.250	0.800
Experience	1.222	0.819
Semen type	1.220	0.819
Training	1.199	0.834
Supplements use	1.121	0.892
AI reliability	1.084	0.923
Gender	1.081	0.925
Government support	1.071	0.933
Education level	1.067	0.937
Extension access	1.062	0.941
Mean VIF	**1.224**	**.**

Source: Author's Computation (2025)

4.3.2 Factors Influencing Adoption of AI Technology

Table 4.17 presents the Probit regression results used to estimate the factors influencing the adoption of AI technology in the study area. The results revealed that ten out of seventeen variables considered and analyzed were statistically significant and influenced AI technology adoption in the study area. Age, education level, experience, milk sales, AI cost, cost of use of bull service, worker's skill on heat detection, semen type, AI reliability and

inseminator availability positively influenced AI technology adoption. Further, only training negatively influenced AI technology adoption in the study area.

Table 4.17: Probit Regression Results on Factors Influencing AI technology Adoption

AI adoption			Coef.	St.Err.	t-value	p-value [95% Conf	Interval]	Sig
Age	0.253	0.102	2.49	0.013	0.054	0.452		**
Gender	0.095	0.186	0.51	0.609	-0.269	0.459		
Education level	0.201	0.03	6.80	0.000	0.143	0.258		***
Experience	0.121	0.059	2.05	0.041	0.005	0.237		**
Group membership	0.154	0.212	0.73	0.468	-0.262	0.569		
Herd size	-0.018	0.045	-0.39	0.696	-0.106	0.071		
Milk sales	0.001	0.000	2.94	0.003	0.000	0.002		***
AI cost	0.542	0.205	2.64	0.008	0.14	0.943		***
Cost of bull	0.001	0.000	1.67	0.094	0.000	0.001		*
Worker's skill	0.198	0.099	1.99	0.047	0.003	0.393		**
Semen type	0.345	0.086	4.03	0.000	0.178	0.513		***
AI reliability	1.862	0.289	6.45	0.000	1.296	2.428		***
Supplements	0.283	0.271	1.04	0.296	-0.248	0.815		
Extension access	-0.332	0.29	-1.15	0.252	-0.900	0.236		
Training	-0.496	0.225	-2.20	0.028	-0.937	-0.054		**
Inseminator availability	0.85	0.241	3.53	0.000	0.378	1.323		***
	-4.239							
	0.696							
Government support	0.204	0.379	0.54	0.59	-0.538	0.946		
Constant 1.095			-3.87	0.000	-6.385	-2.093		***
Mean dependent var			SD dependent var			0.461		
Pseudo r-squared	0.357		Number of obs			332		
Chi-square	145.649		Prob > chi2			0.000		
Akaike crit. (AIC)	300.309		Bayesian crit. (BIC)			372.606		

*** *p<.01,* ** *p<.05,* * *p<.1* denotes significance at 1%, 5% and 10%, respectively.

Source: Author's Computation (2025)

Age was established to have a positive effect and statistically significant at 5% level of significance in explaining the adoption decision of AI technology. This showed that an increase in age by 1 year increases the probability of adopting AI technology by 25.3%. The findings suggests that as farmers get older, they are more likely to adopt AI technology. The argument is that older farmers have more experience, better access to resources, or a

greater willingness to invest in AI technology due to accumulated knowledge. The current finding is in line with those on factors for adoption of artificial insemination technology among pig farmers by Sharma *et al.* (2020) who found out that age of the household head positively and significantly determined the adoption of AI technology in small scale pig production systems in India. The current finding is also consistent with those on factors influencing adoption of AI by smallholder livestock farmers in dryland production systems of Kenya by Abot (2020) who reported a positive influence of age on the adoption of AI technology. Contrary to this finding is that on factors affecting the use of artificial insemination of farmers in dairy farming in Turkey by Özsayın (2020) who reported that age had a negative effect on the use of artificial insemination.

Education level of the household head was found to have a positive effect and statistically significant at 1% level of significance in explaining the adoption decision of AI technology. This showed that a year increase in education is likely to increase the probability of AI technology adoption by 20.1%. Education increases the awareness and promotes attitude change which creates a favourable environment for technology adoption (Mwanga *et al.,* 2019; Okello *et al.,* 2021). Farmers with high levels of education are said to have gained more knowledge and skills and hence the probability of adopting AI technology is higher as compared to those with low levels of education. The current finding are consistent with those on the determinants of utilization of agricultural technologies among smallholder dairy farmers in Kenya by Okello *et al.* (2021) who established that education level positively influenced the utilization of AI. Similarly, a study on adoption of artificial insemination and the intensity of use in Ethiopia by Gebre *et al.* (2022) reported a positive relationship between the households' level of literacy and adoption and intensity of use of AI.

Experience in dairy farming was established to have positive influence on AI technology adoption at 5% level of significance. This means that for every additional year in dairying experience, the likelihood of adopting AI technology increases by 12.1%. Experienced farmers may have observed or learned about the benefits of AI over time which enhance their chances of adopting the technology. Additionally, longer involvement in dairy farming may provide farmers with better financial resources to afford AI services. The current finding is consistent with the findings on factors for adoption of artificial insemination technology among pig farmers by Sharma *et al.* (2020) who found out that farming experience positively and significantly determined the adoption of AI technology in small scale pig production systems in India. The current result is also similar to those on factors affecting the use of artificial insemination of farmers in dairy farming in Turkey by Özsayın (2020) who reported that dairy farming experience had a positive effect on the use of artificial insemination. However, the current findings contradict those on the determinants of utilization of AI services among Ugandan dairy farmers by Kaaya *et al.* (2005) who reported that experience negatively influences the utilization of AI in Uganda. Similarly, a study on adoption and intensity of improved fish feeds use in Western Kenya by Wafula *et al.* (2021) established that experience negatively influenced the intensity of using improved fish feeds in Kenya.

Milk sales was found to have a positive effect and statistically significant at 1% level of significance in explaining the AI technology adoption decision. This implies that a 1 Ksh increase in milk sales is likely to influence the probability of adopting AI technology by 0.1%. Income from milk is an incentive and will determine the probability that a farmer will use AI technology or not. Farmers who receive low incomes are not motivated to use this technology since they do not realize much from dairy farming as compared to those who earn more. The current finding is consistent with the findings by Tefera (2013) who

reported that income from milk sales positively influenced the farmer decision to adopt AI in Ethiopia. A study on multicountry investigation of factors influencing breeding decisions by smallholder dairy farmers in sub-Saharan Africa by Mwanga *et al.* (2018) reported that income from selling dairy products positively influenced the use of AI in Ethiopia and negatively influenced the choice of AI as a breeding option in Tanzania, Uganda, and Kenya.

AI cost was found to be statistically significant at 1% level of significance and positively influenced AI technology adoption by 0.1%. The cost of any dairy technology will always determine its uptake and hence if the technology is affordable it will be embraced by the farmer, and if it is expensive only few farmers will adopt it. The current finding is divergent to the findings on the adoption of improved technologies and profitability of the catfish processors in Ondo State, Nigeria by Olutumise *et al.* (2020) who reported that cost of equipment negatively influenced the decision to adopt and the rate of adopting improved fish processing technologies in Nigeria. The current findings are also inconsistent with those on multi-country investigation of factors influencing breeding decisions by smallholder dairy farmers in sub-Saharan Africa by Mwanga *et al.* (2018) who found out that cost of AI service negatively influenced the choice of AI as a breeding option.

Worker's skill on heat detection was statistically significant at 1% level of significance and positively influenced the probability of adopting AI technology by 19.8%. Successful conception is determined by proper heat timing and timely insemination. Accurate heat detection leads to better reproductive management, shorter calving intervals, and increased milk or meat production. A worker with good skill on heat detection will enhance the chances of a successful conception as compared to the one with poor skills. Additionally,

the worker spends most of his/her time with the cows and monitors the behaviour of the animal and hence is able to detect the possibilities that it is on heat or not.

Semen type was statistically significant at 1% level of significance and positively influenced the adoption of AI technology by 34.5%. There are various types of semen available to the farmers for the select for insemination. It is important to note that farmers who are more literate tend to make decision on the type of semen to be used as compared to less literate farmers. Moreover, farmers who are knowledgeable prefer semen from genetically superior bulls that offer traits such as higher milk production, disease resistance, or faster growth.

AI reliability was statistically significant at 1% level of significance and positively influenced the adoption of AI technology by 186.2%. When farmers believe and trust the capability of a technology to improve the performance of their enterprises are likely to adopt and continue using it. This could be attributed to the fact that farmers like trying out technologies that are believed to benefit them in the long-run. Additionally, farmers are likely to adopt a given technology if it is being promoted by the government and trusted agencies.

Training on livestock production was established to be statistically significant at 5% level of significance and negatively influenced AI technology adoption by 49.6%. Training impacts knowledge to farmers about existing technologies and hence enabling them to use them. The current finding is divergent to those on factors affecting small dairy farmers' adoption and intensity of artificial insemination technology in Ethiopia by Herana and Kumari (2017) who reported that training positively influenced adoption of AI. The current finding is also in line with the finding by Sharma *et al.* (2020) who reported that participation in training and demonstration programmes positively influenced the adoption

of AI technology in small scale pig production systems in India. Moreover, the findings on adoption of artificial insemination service for cattle crossbreeding by smallholder farmers in Ethiopia by Abraha *et al.* (2020) who established that formal training positively influenced AI technology adoption contradict the current result.

Inseminator availability was statistically significant at 1% and positively influenced the probability of adopting AI technology by 85%. This finding could be attributed to the fact that most farmers stated that the inseminator was available when called. The inseminator plays a crucial role in making sure the whole process is successful, and hence insemination will take place if he/she is available. The presence of trained inseminators makes AI technology more accessible and practical for farmers, leading to higher adoption rates. Absence of the inseminator may reduce the chances of a successful conception and this may force farmers to opt to natural mating. Supporting this findings are those on factors affecting adoption of artificial insemination technology by dairy farmers in Tanzania by Temba (2011) who revealed that proximity to AI service providers and access to information were significant factors affecting AI adoption by dairy farmers.

4.3.3 Factors influencing the Intensity of AI Technology

Table 4.18 presents the truncated regression results on the factors influencing the intensity of AI technology adoption in the study area. The table of results shows that nine out of seventeen variables considered and analyzed were statistically significant and influenced the intensity of AI technology adoption on the level in the study area. Among the variables that positively influenced the intensity of AI technology include; age, education level, experience, milk income, and training. Further, group membership, AI cost, worker's skill on heat detection, and availability of the inseminator negatively influenced the intensity of AI technology use.

Age positively influenced the intensity of using AI technology at 1% level of significance. This shows that a year increase in age increases the intensity of AI technology use by 5%. The argument is that as farmers increase in age their experience also adds up. Farmers with a good history with AI use are likely to intensify as opposed to those with bad experiences. The current finding conform those by Chen *et al.* (2020) who reported a positive effect of age on the intensity of tea consumption among men and women in China. The current finding however is divergent to finding by Mahoussi *et al.* (2021) who found out that age square had a negative quadratic relationship with the intensity of use of improved maize seeds in Benin.

Education level was established to have a positive influence on the intensity of AI technology use at a 1% significance level. This implies that for each additional year in education, the intensity of using AI technology increased by 4.2%. This could be attributed to the fact that education improves the knowledge and skills of the farmer. The current finding is consistent with the findings on adoption of artificial insemination technology and its intensity of use in Ethiopia conducted by Gebre *et al.* (2022) who reported that literacy level increases the intensity of AI technology adoption. The current findings also conform to the finding by Mahama *et al.* (2020) who noted that education level positively influenced the extent of AI adoption. However, the current finding contradicts the findings on factor influencing adoption of AI by smallholder farmers in dryland production systems of Kenya by Abot (2020) who found that education level negatively influenced the extent of AI adoption.

Experience was also found to positively influence the intensity of AI technology use at 1% level of significance. This means that a year increase in dairy farming experience is likely to increase the intensity of AI technology use by 5.8%. This could be attributed to the fact

that more experienced farmers tend to continue employing technologies that they perceive beneficial with time. The current findings are consistent with the findings by Olutumise *et al.* (2020) who reported a positive influence of experience on the intensity of adoption of improved technologies and profitability of the catfish processors in Nigeria. The current finding is divergent from the findings by Tefera (2013) who reported that experience of keeping crossbred cattle in the past years had negative effect on the extent of adoption of AI in Ethiopia. The current findings also contradict those on factors influencing adoption decision of AI technology and the extent of adoption by Bayan (2018) who found out that with one additional year older from start of a dairy farm, the probability of adoption and intensity of adoption goes down.

Group membership negatively influenced the intensity of AI technology use by 3.8% at a 5% level of significance. Cooperatives offer a range of benefits to its members including marketing of output, inputs, education and new technologies. The decision to adopt and intensify dairy technologies may be independent of the influence of cooperatives. The current findings is consistent with the finding on the determinants of utilization of agricultural technologies among smallholder dairy farmers in Kenya by Okello *et al.* (2021) who reported a negative influence of group membership on utilization of dairy technologies in Kenya. The current finding is also convergent to those on adoption and intensity of improved fish feeds use in Western Kenya by Wafula *et al.* (2021) who reported that group membership negatively influenced the adoption and intensity of using improved fish feeds. The current finding are inconsistent with the finding on the determinants of artificial insemination use by smallholder dairy farmers in Ethiopia by Tefera (2013) who reported that being a member of dairy cooperative positively influenced the extent of AI use. The current findings are also divergent to the findings on factors affecting adoption of artificial

insemination technology by dairy farmers in Tanzania by Temba (2011) who reported that group membership positively influenced adoption and intensity of AI.

Table 4.18: Truncated Regression Results on Factors Influencing Intensity of AI Technology Adoption

AI production rate	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Age	0.05	0.013	3.80	0.000	0.024	0.076	***
Gender	-0.023	0.016	-1.46	0.145	-0.054	0.008	
Education level	0.042	0.01	4.44	0.000	0.024	0.061	***
Experience	0.058	0.017	3.40	0.001	0.025	0.091	***
Group membership	-0.038	0.017	-2.17	0.03	-0.072	-0.004	**
Herd size	-0.003	0.004	-0.76	0.448	-0.011	0.005	
Milk sales	0.000	0.000	2.07	0.039	0.00	0.00	**
AI cost	-0.029	0.016	-1.80	0.071	-0.06	0.002	*
Cost of bull	0.000	0.000	0.75	0.456	0.00	0.00	
Worker's skill	-0.016	0.009	-1.83	0.067	-0.034	0.001	*
Semen type	-0.003	0.007	-0.38	0.702	-0.016	0.011	
AI reliability	-0.019	0.02	-0.95	0.343	-0.057	0.02	
Supplements use	0.03	0.023	1.27	0.204	-0.016	0.075	
Extension access	-0.021	0.023	-0.93	0.353	-0.067	0.024	
Training	0.056	0.021	2.61	0.009	0.014	0.098	***
Inseminator availability	-0.048	0.021	-2.26	0.024	-0.09	-0.006	**
Government support	0.02	0.031	0.66	0.506	-0.04	0.08	
Constant	1.096	0.09	12.18	0.000	0.92	1.272	***
Sigma	0.137	0.005	25.77	0.000	0.127	0.147	***

Mean dependent var		1.021	SD dependent var			0.144	
Number of obs	332	Chi-square	33.543	Prob > chi2	0.014	Akaike crit.	
(AIC) -338.117							

*** *p<.01,* ** *p<.05,* * *p<.1* denotes significance at 1%, 5% and 10%, respectively.

Source: Author's computation (2025)

Training was established to have a positive influence on the intensity of AI technology use at a 10% level of significance. This means that attending trainings increases the intensity of AI technology use by 5.6%. The argument is that farmers who have been trained have better access to information and agricultural knowledge about dairy farming as opposed to

their non-trained counterparts. The current finding is consistent with the findings on factors affecting small dairy farmers' adoption and intensity of artificial insemination technology in Ethiopia by Herana and Kumari (2017) who reported that access to AI training positively influenced intensity of AI in Ethiopia. The current finding also conforms to the findings by Gebre *et al.* (2022) who reported that access to training positively influences the intensity of AI technology adoption in Ethiopia. However, a study by Dumara and Zenbaba (2020) established that attendance in training had a positive and significant effect on the adoption and intensity of adoption of malt barley technology in Ethiopia.

Inseminator availability was found to have a negative influence on the intensity of AI technology use by 4.8% at a 5% level of significance. This could be attributed to some cases of dishonesty by the inseminators. Farmers who have experienced any form of cheating from the service providers are less likely to intensify the adoption of AI technology (Kaaya *et al.,* 2005). The findings by Abot (2020) on factor influencing adoption of AI by smallholder farmers in dryland production systems of Kenya, who reported that dishonesty from the service providers negatively influenced the intensity of AI adoption supports our findings.

4.4 Hypothesis Testing

The following section explains the hypothesis testing for each objective of the study.

H_{01}: The null hypothesis of the first objective which stated that social factors do no significantly influence AI technology adoption and intensity among smallholder dairy farmers in AlegoUsonga sub-county was rejected because social factors such as age, education level, and experience had significant influence on AI technology adoption and intensity in the study area.

H_{02}: The null hypothesis of the second objective which stated that economic factors do no significantly influence AI technology adoption and intensity among smallholder dairy farmers in Alego-Usonga sub-county was rejected because economic factors such as milk sales, and cost of AI had significant influence on AI technology adoption and intensity in the study area.

H_{03}: The null hypothesis of the third objective which stated that technical factors do no significantly influence AI technology adoption and intensity among smallholder dairy farmers in Alego-Usonga sub-county was rejected because technical factors such as worker's skill on heat detection, semen type, and AI reliability had significant influence on AI technology adoption and intensity in the study area.

H_{04}: The null hypothesis of the fourth objective which stated that institutional factors do no significantly influence AI technology adoption and intensity among smallholder dairy farmers in Alego-Usonga sub-county was rejected because institutional factors such as training, and inseminator availability had significant influence on AI technology adoption and intensity in the study area.

CHAPTER FIVE

SUMMARY OF FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

5.1 Summary of the Findings

The main purpose of the study was to analyze factors influencing the adoption and intensity of AI technology in Alego-Usonga, Siaya County. The study found that most small-scale dairy farmers adopting AI technology were over 40 years old, with 40.96% aged 40–49 and 47.29% above 50, with a slightly higher proportion of female farmers (54.22%) than male farmers (45.78%). Education levels varied, with 25% lacking formal education, 38.86% completing primary school, 18.67% reaching secondary school, and 17.47% attaining higher education. Farming experience played a role in AI technology adoption, as 68.67% had over five years in dairy farming, while only 3.31% had less than a year. However, most farmers (60.54%) were not members of any farmer group.

On average, households in the study area had three cows, with daily milk sales ranging from KSh. 60 to KSh. 2,450, reflecting variations in productivity and income. AI costs were relatively high, with most farmers paying over KSh. 2,000 per service. Bull service costs averaged KSh. 854, ranging from KSh. 200 to KSh. 3,000. Nearly half (49.35%) of small-scale dairy farmers rated workers' heat detection skills as good, while 47.19% found them poor. Most farmers (71%) were unaware of the semen type used, with 23.38% using sexed semen. AI reliability was a concern, as 54.55% considered it unreliable. Additionally, 86.45% provided supplement feeds to their cows. Most small-scale dairy farmers (87.05%) had access to extension services, and

71.99% attended livestock production training. Government support was minimal, with over 92% of adopters and 95% of non-adopters receiving none. Additionally, 87.01% reported that an inseminator was always available when needed.

The study identified several factors influencing AI adoption. Age, education, experience, milk income, AI cost, heat detection skills, semen type, AI reliability, and inseminator availability positively influenced AI adoption. Conversely, training on livestock production negatively affected AI adoption. Factors influencing AI intensity included age, education, experience, and training on livestock production, which positively impacted AI use. However, group membership and inseminator availability negatively influenced AI intensity.

5.2 Conclusions

The study highlights key factors influencing AI adoption among small-scale dairy farmers, emphasizing the role of age, education, farming experience, and economic considerations. Older and more experienced farmers were more likely to adopt AI technology, while education and experience played a crucial role in both adoption and intensity of AI technology use.

Despite having relatively small herds, farmers exhibited significant variations in milk productivity and income, with high AI costs presenting a financial barrier. Challenges such as poor heat detection skills, limited awareness of semen types, and concerns over AI reliability further impacted adoption rates.

Access to extension services and training was generally high, yet government support remained minimal. Interestingly, while inseminator availability was not a major issue, group membership and livestock production training negatively influenced AI intensity, suggesting that certain collective or traditional farming practices may deter AI usage.

The findings underscore the need for targeted interventions, including improved farmer education, financial support, and enhanced AI service reliability, to increase AI adoption and maximize its benefits in small-scale dairy farming.

5.3 Recommendations

Based on the findings from the study, the following recommendations were suggested:

- Improve farmer education through introduction of adult learning sessions for farmers in a bid to improve their literacy levels. The benefit will be increased awareness and positive impact on adoption of artificial insemination technology in the study area.
- Farmers should be encouraged to form more farmer groups by promoting the benefits that are likely to be accrued when people form groups, such as markets for their outputs, education and training, and dissemination of dairy technologies such as AI.
- Farmers should enhance the skills of their workers by allowing them also to attend trainings on livestock production and AI technology.
- Enhance training effectiveness by conduct training needs assessments before the trainings are carried out so as to capture the farmers' interest together with the environment.
- The government should support AI activities by subsidizing the cost of AI and feeds to individual farmers and groups, funding trainings and workshops, and provide capacity building for the trainers.

5.4 Suggestions for Further Research

The current study was limited only to Alego-Usonga Sub-County; therefore, similar research should be conducted in other Sub-Counties and other regions of the country to

examine the effect of studied variable on the adoption and intensity of AI adoption. An assessment of the impact of AI technology on household income is also necessary so as to determine the net benefit of AI technology in the study area. Further, given that training was hypothesized to have a positive influence on AI technology adoption but results revealed a negative effect, hence the study suggest an investigation of the effect of trainings on AI technology adoption in the study area.

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APPENDICES

APPENDIX I: QUESTIONNAIRE

I am a postgraduate student of Moi University; conducting a research on "Analysis of Factors Influencing the Adoption and intensity of Artificial Insemination Technology among smallholder Dairy Farmers in Alego-Usonga Sub-County, Siaya County". You have been selected to participate as a smallholder dairy farmer. The information that you will provide will be treated with utmost confidentiality for the purpose of the study with anonymity observed Yours Faithfully

Gislar Awuor

SECTION A: BACKGROUND INFORMATION

1. Please indicate your age bracket?

1. 20-29 years [ ]
2. 30-39 years [ ]
3. 40-49 years [ ]
4. Above 50 years [ ]

2. Please indicate your gender

Male [ ]

Female [ ]

3. Please indicate your education level

1. No formal education [ ]

2. Primary school [ ]

3. Secondary school [ ]

4. College and above [ ]

4. What is your average income from sale of milk?

5. What are your other sources of income?

6. How long have you been in practicing dairy farming?

    1. Less than one year [ ]
    2. 1- 5 Years [ ]
    3. More than 5 years [ ]

7. Are you a member of any farmers group?

Yes [ ]
No [ ]

If yes, state the benefits…….

8. How many times have you used AI for the last 5 years?

None [ ] Less than 3 [ ] More than 3 [ ]

SECTION B: ECONOMIC FACTORS ON THE A.I ADOPTION

9. Do you prefer AI or the natural methods of breeding?

AI [ ] Natural [ ]

10. How many cows do you keep in your farm?

11. What is the cost of AI administration? (Inclusive of semen and labor)

1. Between 0 – 1000 [ ]

2. 1000 – 2000 [ ]

3. Above 2000 [ ]

12. What is the cost of using other breeding methods i.e. use of a bull?

SECTION C: TECHNICAL FACTORS

13. How do you rate your workers skills on heat detection?

1. Poor [ ] 4. Excellent [ ]

2. Good [ ]

3. Very good [ ]

14. What are the alternative sources of semen breeding?

15. Do you think the use of AI technology is reliable?

Yes [ ]

No [ ]

Comment

SECTION D: INSTITUTIONAL FACTORS

16. Do you access extension services?

Yes [ ]

No [ ]

If yes, state the number of times?……

17. Do you attend trainings of livestock production?

Yes [ ]

No [ ]

If yes, how is it useful?.....

18. Whenever you call the inseminator do you get him/her?

Yes [ ]

No [ ]

If yes, how do you rate the inseminator in terms of availability?

1. Daily [ ]

2. Once a week [ ]

3. Hardly available [ ]

APPENDIX II: MAP OF SIAYA COUNTY

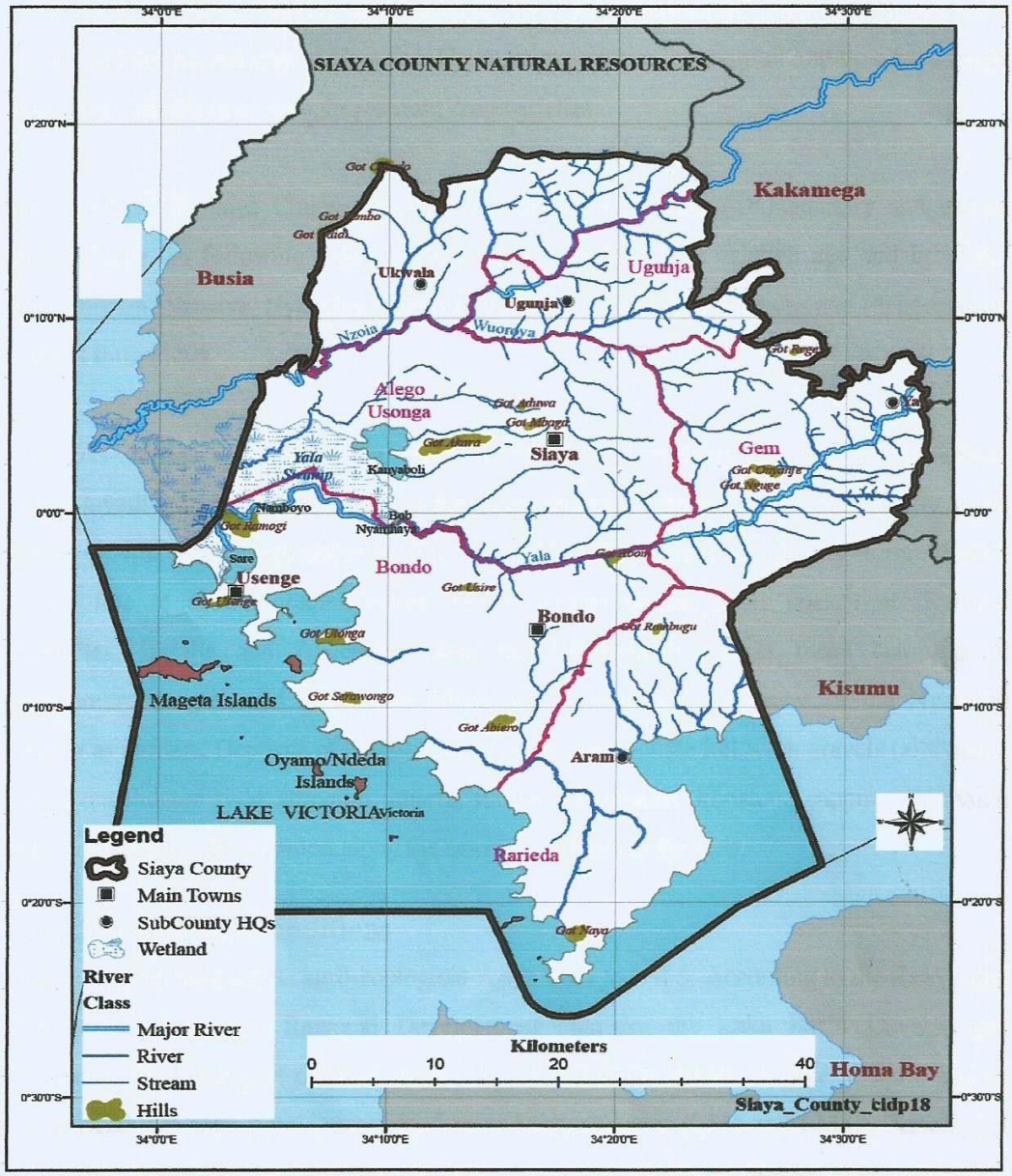

Figure 2: County Natural Resources

Page 3

Source: Siaya county CIDP (2018-2022)

ANNEX I: RESEARCH PERMIT

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