THE IMPACT OF ADOPTING ARTIFICIAL CATTLE INSEMINATION TECHNOLOGY ON SMALLHOLDER FARMERS' WELLBEING: THE CASE OF YEM SPECIAL DISTRICT, SOUTHERN ETHIOPIA

MSc. THESIS

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ADVISORS' APPROVAL SHEET

This is to certify that the thesis entitled ‘‘The impact of adopting artificial cattle insemination on smallholder farmers wellbeing: the case of Yem special district, submitted in partial fulfillment of the requirements for the degree of Master's with specialization in Developmental Economics, Department of Economics, College of Business and Economics/School of Graduate Studies, and has been carried out by Abebe Eshetu Lemma; ID. No BEGR/002/13, under my supervision. Therefore, I recommend that the student has fulfilled the requirements and hence here by can submit the thesis to the department.

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EXAMINERS' APPROVAL SHEET

We, the undersigned, members of the Board of Examiners of the final open defense by Abebe Eshetu have read and evaluated his thesis entitled ‘‘the impact of adopting artificial cattle insemination by smallholder farmers on their wellbeing in case of SNNPR Yem special district, and examined the candidate. This is, therefore, to certify that the thesis has been accepted in Partial fulfillment of the requirements for the degree masters of Science in economics specialization in developmental economics.

Name of the Chairperson	Signature	Date
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Name of Internal Examiner	Signature	Date
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Badassa Wolteji (PhD.)	________	15 Nov, 2022

Final approval and acceptance of the thesis is contingent upon the submission of the final copy of the thesis to the School of Graduate Studies (SGS) through the Department/School Graduate Committee (DGC/SGC) of the candidate's department.

Thesis approved by

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DECLARATION

I hereby declare that the thesis entitled as the ‘‘impact of adopting artificial cattle insemination technology on smallholder farmers wellbeing: the case of Yem special district, Ethiopia’’ is result of my own effort. I have prepared the thesis independently with the guidance and support of the research advisors. The study has not been submitted to the award of any degree in any collage. It is submitted for the collage in partial fulfillment of the requirements for the Degree of Master of Science in Development economics.

Name of the student: Abebe Eshetu Lemma

Signature: ___________________________________

Date of submission: ___________________________

DEDICATION

This thesis is especially dedicated to my family who fulfilled my desire and supported my success.

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ACRONYMS/ABBREVIATIONS

AI	Artificial Insemination
AITs	Artificial Insemination Technologies
ATE	Average Treatment Effect
ATT	Average Treatment on the Treated
CC	Contingency Coefficient
CIA	Conditional Independence Assumption
DA	Development Agent
DDA	Dairy Development Agency
EAIR	Ethiopian Institute of Agricultural Research
FHH	Female Headed Household
FTAI	Fixed Time Artificial Insemination
GDP	Gross Domestic Product
ILDP	Integrated Livestock Development Project
ILRI	International Livestock Research Institute
MHH	Male Headed Household
NAIC	National Artificial Insemination Center
NARS	National Agricultural Research System
NMA	National Metrological Agency
NNM	Nearest Neighbor Matching
PSM	Propensity Score Matching
SB	Standardized Bias
SIDA	Swedish International Development Agency
SNNPR	Nation Nationality People Region
TLU	Tropical Livestock Unit
UHT	Ultra High Temperature
USAID	United States Agency for International Development
MASL	Meter above sea level
YSWAO	Yem Special Woreda Agricultural Office
YSWFEDO	Yem Special Woreda Finance & Economic Development Office
YSWHO	Yem Special Woreda Health Office

ABSTRACT

This study investigated the impact of adopting artificial cattle insemination technology on smallholder farmers' well-being in Yem special district. For quantitative analysis, both adopter and non-adopter respondents were drawn and cross-sectional survey data was collected from 361 households. The statistical models distinctively, binary logistic regression, Tobit, and propensity score matching methods were used to determine factors affecting the adoption of AI technology, the extent of adoption, and the impact of AI technology adoption on smallholder farmers' well-being respectively. The binary logit result revealed that educational level, family size, livestock holding (TLU), timely availability of AI service, perception, and access to grazing land are significant variables affecting the adoption of AI technology. The PSM method was checked for covariate balancing with a standardized bias, t-ratio, and joint significance level tests. Furthermore, sensitivity analysis of the estimated adoption effect to unobserved selection bias was checked using the Rosenbaum bounds procedure. The adoption of AI have a significantly positive impact on adopter households wellbeing. The finding indicates that the adoption of the technology had increased the milk income, livestock income, and total consumption by about 62.742, 31.215, and 11325.694 birrs per year respectively, which is significant at a 1% probability level on average compared to the non-adopters. What about the impact based on the findings, the study suggests that strengthening the promotion of AI technology adoption have a crucial role in improving the well-being of households in the study area. In doing so, managing the possible influencing factors that affect the adoption of AI technology and adoption intensity should be a prerequisite.

Keywords: *Artificial insemination, Propensity Score matching, Yem special district.*

CHAPTER ONE

1. INTRODUCTION

1.1. Background of the Study

The economic and social importance of livestock is known both at the national and household levels. The sub-sector contributes an estimated 12% to total GDP and over 45% to agricultural GDP (Muuz, 2018). Ethiopia livestock master plan brief Livestock is a primary livelihood source for many low-income rural farmers particularly in Sub-Saharan African countries (Aynalem *et al*., 2011). In line with this, livestock production contributes up to 80% of farmers' income and 16% share in export of the country's economy (Muuz, 2018) . However, the contribution of the sub-sector is below the expected level, it has a practical impact on the lives of people in terms of income and employment generation and by enhancing the provision of nutritional security it improves the well-being of society (Yohannes, 2014).

The economic well-being of farm households depends on their resources, production and employment levels, and the ability of income to meet consumption, savings, and other household needs. Different works of literature and scholars discuss milk income, income from sales of animals, and consumption expenditure are indicators or measures of the well-being of livestock-growing households (Yohannes, 2014). Holding high productive performance dairy cow breeds can assure an increased income that improves farmers' household well-being. Using artificial insemination technology reasons an appreciation for the production of milk, butter, yogurt, meat, and other dairy products that can bring more income and well-being to the community.

According to (Azage et al., 2012) and (Baban *et al*., 2017), livestock output uses, subsistence consumption by the livestock holders, direct supply of inputs, cash income through sales of live animals or their output, savings and investment, and social functions such as paying bride wealth or providing animals for communal feasts.

According to (Elisa et al., 2015), livestock products uses as an input supply such as fertilizer and animal draught, and the capacity to comply with a set of social rules and obligations.In many rural regions, in special where financial markets are absent or non-existent (Elisa et al., 2015), livestock stocks or herds are a source of asset accumulation and a measure of prosperity/wealth. Livestock stocks or assets can be mobilized at any time, satisfying planned expenditures such as children's school fees and the bride's wealth or unplanned expenses such as the illness and death of family members.

This livestock asset could be seen as a “bank account” and it is also an important source of family savings that can be used in years of low crop production. Reducing income insecurity and household vulnerability is an important source of security increase (Baban *et al*., 2017). Generally, according to the above discussions adopting livestock technologies, especially artificial cattle insemination has a direct contribution to farm households' well-being.

This importance is pronounced in pastoral areas, both directly in primary production, and indirectly through the contribution of livestock to household assets and food security which helps to assure their well-being (Sintayehu et al., 2010) as cited by (Yohannes, 2014).

Despite, the all-around contribution of livestock to household wellbeing; its productivity is very poor in Ethiopia due to the meager adoption participation of dairy technology (Zegeye, 2003). Around 99% of the cattle population in Ethiopia is indigenous and only the rest is improved. Most of the local indigenous cattle belong to the Zebu type. Because of this productivity is very low and fails to support the demands of the continuously mounting human population (Tadesse et al., 2016). Hence to boost the productivity of the sector; introducing artificial insemination and increasing the adoption level of farmers are the main practices engaged to get better the well-being of the farmers (Dehinenet et al., 2014).

The productivity of local livestock is a major constraint in dairy development. In indigenous herds, the genetic potential for milk production is very low and has no power to support the well-being status of the farmers as compared to improved breeds (Aynalem *et al*., 2011). As a result, the important perspective for smallholder farmers' income generation and employment opportunities from the high-value dairy products, the development of the dairy sector, and the promotion of the breed type contribute immensely to improving farmers' well-being (Ahmed *et al*., 2004). Conversely, the policy design and effective management of extension programs, and information on the impact of AI technology on the well-being of households are very important and would help to come up with workable recommendations to improve the performance of the sector. Recognizing this, adopting artificial insemination technology is broadly considered to address household well-being (Yohannes, 2014).

Therefore, this research is aimed to examine the impact of adopting artificial cattle insemination technology on smallholder farmers' household well-being as well as to investigate factors that determine the adoption of AI technology and asses the extent of the adoption in Yem special district.

1.2. Statement of the problem

The sector of livestock in Ethiopia has the potential to improve the household well-being of both rural and urban peoples and it contributes to the country's GDP growth (Muuz, 2018). Holding improved livestock husbandry contributes directly to household well-being through the provision of cash income and ensuring food security *(*Smith *et al*., 2013). The adoption and efficient use of artificial insemination that improves the productive performance of the dairy cow is vital for income generation, poverty reduction, and nutritional security in Ethiopia. And this increase in income can ensure improvement in the well-being of the farm households (Alary et al, 2011) and (Dehinenet et al., 2014).

In terms of its contribution to better livelihood or household wellbeing livestock technologies especially artificial insemination technology is less adopted in developing countries like Ethiopia and the results obtained from the sector are not satisfactory compared to developed countries (Marshall, 2014). In Ethiopia, some socio-economic, institutional, behavioral, situational, and technical factors make the service more difficult to offer (Azage and Hoekstra, 2013). According to the Ministry of Agriculture, there are only 30,000 crossbreed dairy cows in Ethiopia, in other words, less than 1 percent of the 34.5 million cattle populations of Ethiopia are exotic or crossbred dairy cows. Quite the reverse, Kenya has around 3 million crossbred dairy cows (Kebebe, 2018).

According to (Azage and Hoekstra, 2011) as cited by (Yohannes, 2014), the IPMS (Improving the Productivity and Market Success of Ethiopian Farmers) project identified the lack of genetically improved animals as a key constraint in dairy production. The adoption of dairy technologies mainly the provisions of artificial insemination that amplify the productivity of livestock is instrumental for achieving economic growth, food security, and poverty alleviation that leads to better household wellbeing (Yohannes, 2014).

The well-being of livestock-growing households depends on their income resources, production and employment levels, and the ability of income to meet consumption, savings, and other household needs. In various studies, like (Samuel et al., 2016), the impact of technology adoption on household wellbeing can be measured based on different aspects of well-being indicators that are associated with an improved standard of living such as food, clothing, shelter, health care, education, and recreation. However, in this study Milk income, income from animal sales, and total consumption /food and non-food/ were used to measure the well-being of artificial cattle insemination using households.

In Yem special woreda livestock is the mainstay of the livelihood of the majority of the population by giving draft power supply for crop production and transport, as a source of food like meat, milk, yogurt, and source of cash income. Despite their all-around advantage of livestock in the district, its productivity has remained very low and it is dominated by local breeds with low productive performance.

Numerous research findings have confirmed that the adoption of dairy technology like artificial insemination could lead to significant enhancement in livestock production that encourages the transition from low production subsistence to high productivity (Amanuel, et al, 2018); (Melesse and Jemal, 2012) and (Baker, 2018). These researches have been describing the role of adopting artificial insemination on dairy farm productivity and its capacity for income generation.

In addition to this, the main determinants of adopting artificial insemination technology have been identified in these studies. The results of the study have identified as Socioeconomic, Behavioral, situational, institutional, farm characteristics, and demographic profiles are factors significantly affecting the adoption participation of the farm households. In an attempt to develop the dairy production system of Ethiopia, using technologies especially AI is vital for structural change in the productive performance of dairy cows (Gillespie et al., 2004). Using artificial insemination assists to generate better income that supports the user's well-being (Olynk and Wolf, 2008).

Artificial cattle insemination is implemented in Yem special district since 2006 to scale up dairy production and generate higher income from the sector. However, according to the information from Yem special district agriculture office report 2019 and different files documented regarding artificial insemination shows the impact of the technology on the adopter household in the district is not examined and no effort had been made to evaluate the impact of the program.

Moreover, the factors that hamper adoption participation and adoption intensity are not identified; hence creating knowledge and information gap that needed to be filed. Generally, no study has been done to examine the impact of artificial cattle insemination technology on the adopters' household well-being in the district at all. Recognizing these; some questions require rigorous assessment which adheres to what factors determine the adoption of artificial insemination in the study area ?. Does the adoption of such technology affect the well-being status of the household? And a question regarding the intensity of the adoption among the adopters in the study area still waiting for a concrete solution.

Therefore, the present study is expected to examine the impact of adopting artificial cattle insemination technology on the well-being of smallholders household and is designed to bridge the existing knowledge and information gap related to the factors that affect the adoption of the technology and the extent of the adoption in the study area. The impacts of adopting the technology were measured in multi-dimensional levels of household wellbeing using the propensity score method (PSM).

1.3. Research Questions

1. What are the factors that affect the adoption of artificial insemination technology in the study area?

2. What is the intensity or the extent of artificial insemination technology adoption in the study area?

3. What are the impacts of adopting artificial cattle insemination technology on the well-being of the household in the study area?

1.4. Research Objectives

1.4.1 General Objectives

The general objective of the study is to assess the impact of adopting artificial cattle insemination technology on smallholders’ household Well-being and to identify the determinants of the adoption in the special district.

1.4.2. Specific Objectives:

With the above general objective, the study has attempted to realize the following specific objectives.

1. To investigate the factors that determine the adoption of artificial insemination technology in the study area.
2. To examine the extent/intensity of the adoption of artificial insemination technology in the study area.
3. To evaluate the impact of adopting artificial insemination on the smallholder farmers' household well-being in the study area.

1.5. Significance of the study

Studying the impact of adopting artificial insemination technology on household well-being, particularly in the community of Yem special woreda at large applauded. Therefore, the output of this research has shown how the adoption of artificial insemination affects the well-being of the adopter households. And the factors that hinder the adoption of the technology and its adoption extent in the study area were identified. In addition, this study helps the government and stakeholders in terms of providing insights, knowledge, and due attention to better design development programs and projects for the farmers that improve their well-being options. Policymakers also benefit from the research output because they require information to formulate policies about farmers' technology adoption and identify major factors that influence the uptake of the technology. Furthermore, this study also serves as literature for researchers who desired to conduct further studies on a similar topic in the future. In general, the study was expected to provide vital information for different stakeholders to develop sustainable strategies that decrease drawbacks and other associated issues in this study.

1.6. Scope of the study

Since it is not possible to study factors and impacts of all livestock technologies on farmers' well-being, this study considers only the impact of adopting artificial cattle insemination on smallholder farmers' household well-being in Yem special district Ethiopia. Factors like socio-economic, institutional, and demographic that determine the impact of adopting artificial insemination on household well-being were considered in this study. This study focused on households who adopted artificial insemination technology and potential dairy-producing kebeles.

1.7. Limitation of the Study

This study has faced constraints like lack of data coverage and information limitations due to the scarcity of a similar type of literature widely discussing the adoption decision, the extent of adoption, and its effect on household wellbeing, particularly in the study area.

The study has covered 8 of the 25 artificial insemination technology adopting kebeles from which both treatment and control groups of 361 total sample households were drawn. Therefore, data collection for the survey was not an easy task and it consumed more time and energy. The topography of the study area is highly difficult and that road accessibility especially from cluster to cluster in the kebele during data collection and interview was another challenge faced in this study. As a result, more data collectors and time were required and consumed through the process. Besides, rural households in the local area are very shy, due to this more time and human resources were required to get relatively accurate information during the interview.
Finally, the study was limited to only the special district due to limited resources and time, in fact, it would be fundamental if more districts and households from nearby zones were included to produce much more reliable data that address all outcome variables of household well-being.

1.8. Organization of the Study

This study was organized into five chapters. The first chapter is stating the introduction, which comprises the background information, problem statement, objectives, scope, and significance. Chapter two presents a literature review that includes concepts of artificial insemination and dairy products globally, in Africa, in Ethiopia as well as in Yem Special district; constraints to adopting artificial insemination and the economic impact of artificial insemination, empirical studies, and conceptual frameworks. Chapter three introduces the methodology, which includes a description of the study area, source, and methods of data collection and analysis as well. Chapter four brings the result and discussion of the research outcomes and finally chapter five comes up with a conclusion and recommendations.

CHAPTER TWO

REVIEW OF RELATED LITERATURE

This section draws on literature in the area of the adoption of artificial insemination for cattle breeding and its impact on household well-being. The chapter reviews literature by other scholars especially studies touching on the implementation of artificial cattle insemination services and its impact on household wellbeing. The chapter also addresses the history of artificial insemination technology, the theoretical framework on which the study builds, and then presents an empirical review of literature on the different measurements of household well-being.

2.1. Theoretical Review

2.1.1. Definition and concept of technology adoption

According to the studies on the innovation diffusion model by (Feder et al., 1985), adoption is an integration of innovation into farmers' activity for a while, in the view of this author farmers may not be long in the adoption process because of different constraints like institutional, personal and social reason. According to (Carr, 1999), technology adoption is a stage of selecting a technology by an individual or group of people. On the other hand, the theory regarding technology adoption is a process of members or groups of a social system communicating an innovation through a certain channel (Feder et al., 1985).

The adoption process is the change that takes place within the individual about innovation from the moment that they first become aware of the innovation to the final decision to use it or not. However, as it is stated by (Yohannes, 2014), adoption does not necessarily follow the suggested stages from awareness to adoption; trial may not be always practiced by farmers to adopt new technology. Farmers may adopt the new technology by bypassing the trial stage. (Dasgupta, 1989), indicates that the decision to adopt an innovation is not normally a single instantaneous or immediate action, it involves a process. Adoption is a decision-making process, in which an individual goes through several mental stages before making a final decision to adopt an innovation (Berhe, 2006). In another definition developed by (Rogers, 1983), adoption is defined as a mental process through which an individual passes from knowledge of innovation from knowing or hearing about the innovation to the final decision to adopt or reject the technologies. This shows that the adoption process takes time for acceptance by farmers (Rogers, 1983).

2.1.2. The concept of household Wellbeing

Well-being can be understood as how people feel and how they function, both on a personal and a social level, and how they evaluate their lives as a whole. However, it is important to realize that well-being is a much broader concept than moment-to-moment happiness. While it does include happiness, it also includes other things, such as how satisfied people are with their life as a whole, their sense of purpose, and how in control they feel (Ashok *et al*., 2002).

The economic well-being of farm households depends on their resources, production and employment levels, and the ability of income to meet consumption, savings, and other household needs. According to (Ashok *et al*., 2002) farm household economic well-being is affected both by the level of income and wealth available to the household and by its influence on the consumption of goods and services. In this context, well-being has both an absolute component, which compares income and wealth to a selected standard, and a relative component, which measures the ability of households to meet consumption needs.

Traditionally, assessments of farm household economic well-being have had a uni-dimensional focus: determining how income levels of farm households compared with incomes of nonfarm households. Well-being comes from many different factors like how one earns, where one lives, what one eats, how much is eaten, the things acquired and used daily, whether one goes to school or not, and whether one sees a doctor when sick or not (Almas, 2016).

Computationally, there are two broad approaches to defining well-being. These include the welfarist and non-welfarist approaches. The welfarist approach defines well-being in terms of the level of utility attained by an individual. This approach attaches great importance to an individual's perception of what is useful to him or her. According to the non-welfarist approach, well-being is defined as independent of the individual's perception of it. This approach depends on what planners consider desirable from a social point of view (Aigbokhan 2008).

According to (Almas, 2016), in several eastern African countries measures of well-being are considered to take a broad view of well-being compared with a view that focuses only on material well-being. The study shows that several other indicators including individual socioeconomic characteristics and ethnicity also play an important role in the overall well-being and its components. The issue of multidimensional well-being is extended to an analysis of social well-being in rural Ethiopia.

2.1.3. Definition of Artificial Insemination

Artificial insemination has been defined as a process by which sperm is collected from the male, processed, stored, and artificially introduced into the female reproductive tract for conception or genetic improvement (Webb, 2003). Semen is collected from the bull, deep-frozen, and stored in a container with Liquid Nitrogen at a temperature of minus 196 degrees Centigrade and made for use. Artificial insemination has become one of the most important techniques ever devised for the genetic improvement of farm animals, (Webb, 2003; Bearden *et al.*,2004).

2.1.4. History of Artificial Insemination

The first successful artificial insemination was performed in Italy by physiologist and priest Abbe Lazzaro Spallanzani in 1780 with successful artificial insemination in a dog and over 100 years later, in 1890, it was used for horse breeding (Webb, 2003) as cited in (Habtamu *et al.*, 2013). However, it was only in the early 1900s that a Russian scientist named E.I. Ivanhoe accomplished the first successful AI in cattle.

Mass breeding of cows via artificial insemination was first accomplished in Russia where 19,800 cows were bred in 1931(Webb, 2003).

The use of AI in animal reproduction was originally introduced for sanitary reasons (to prevent the spread of sexually and non-sexually transmitted diseases) (Kaaya et al., 2005). However, farmers soon recognized that AI was the method of choice for the rapid introduction of valuable genes into a population to improve its production traits. When cryopreserved (CP) semen became available, the economic advantages provided by improved fertility rates and accelerated genetic progress became fully clear.

Artificial insemination has become the foundation for expanded breeding schemes such as estrus synchronization programs (synchronized breeding, including timed AI), embryo transfer, the use of sexed semen, cloning, and transgenic. The use of AI, especially in dairy cattle, has become routine and most of it is practiced by the producers or herd managers themselves to increase the productive performance of the livestock especially dairy cattle (Peter and Farin, 2007).

2.1.5. Artificial insemination in Africa

The vast majority of African countries offer farmers some opportunities to use AI, even if it is sometimes on a limited scale. According to (Bonadonna, and Succi, 1980), for Eastern European countries and developing countries including Africa, a crude estimate was made of the relative importance of AI activity in the developing world as compared with its role in the industrialized world.

Of the total number of AI applications carried out, 41 percent were performed in developed countries and 42 percent in Eastern European countries, while AI activity in the developing world represented only 17 percent (Yohannes, 2014). Technical difficulties are already well known. Solutions exist for some, although their economic feasibility must be seriously investigated, such as that of using oestrus synchronization to overcome estrus detection problems.

Techniques are not yet available for estrus detection in the isolated female or for freeze-dried semen (which would solve storage problems). However, these are not the main reasons for the slow increase in the use of artificial insemination in developing countries. The main reason is the lack of sound long-term breeding strategies that would improve the farmers' profits in the short term without destroying the indigenous genetic resources in the long term (Chupin .D, 2010).

2.1.6. Artificial insemination in Ethiopia

In Ethiopia improving the cattle breed is an important component of dairy farming that promotes productivity and improves household well-being. The favorable agroecological condition of the country is suitable for dairy production in rural, peri-urban and urban areas. On the other hand, the consumption of dairy products in all settings is very high. However, productivity is generally limited. This results in a shortage of supply of dairy products as compared to the demand of the population and requires spending a lot of currency to import dairy products abroad (Tegegne *et al*., 2010).

The annual growth of milk production rate in the country is 1.2 percent falls behind the annual human population growth estimated at 3 percent (Levitt *et al*., 2011). The sector is dominated by traditional milk production systems and indigenous breeds of low genetic potential for milk production accounting for about 97 percent of the country’s total annual milk production in Ethiopia (Felleke et al., 2010). In Ethiopia indigenous cow's national average milk yield per day is 1.35 liters and the per-capita milk consumption in the country is about 19.24 kg/year respectively. (CSA /Central Statistical Agency, 2010/2011) suggested that the indigenous cattle breeds accounted for 99.1%, while the hybrid and pure exotic breeds accounted for about 0.72% and 0.9% respectively.

Generally adopting quality cattle breeds with high productive performance can ensure household wellbeing through its contribution to growth in income (Gizaw *et al.*, 2016). The AI service in Ethiopia is lower due to poor heat detection, improper timing of insemination, and embryonic mortalities besides inadequate infrastructure, and managerial and financial constraints (Shiferaw *et al*., 2003). Under the Ethiopian context, livestock, particularly adapted cattle genetic resources are an important element in the well-being of many resource-poor farmers living in a wide range of production systems and contribute more than marketable products that are considered in economic statistics (Kefena *et al*., 2011).

2.1.7. Determinants of AI technology adoption

The objective of the artificial insemination program is to increase livestock productivity through the creation of awareness and technology adoption. Adoption of any agricultural innovation can be measured in two ways: In terms of the number of farmers who adopt the innovation and in terms of the total area on which the innovation is (Samuel et al., 2016).

Different studies conducted in different countries revealed that demographic, social, and economic factors affect the adoption of improved agricultural technologies more specifically artificial insemination technologies and a few of those studies will be discussed below. As cited (Samuel et al., 2016), and (Kaaya et al., 2005) used the Tobit model to reveal factors that influence the extent of adoption of artificial insemination (AI) services and found the education level of the farmer, years of awareness of the AI technology, total farm size, milk production and sales, extension visits per year and quality of AI services provided to the farmers were positively associated with adoption and use of AI technology.

(Dehinenet *et al*., 2014) also reported that both age of the household and off-farm activities are significantly related to the adoption of improved dairy technologies. According to (Samuel et al., 2016) family size, farming experience, availability of communication services, availability of training, and accessibility of credit and saving institution affects the adoption of the technologies positively and significantly.

As stated in the study by (Minale *et al*., 2015) the extension service has an important role in transferring the technologies to the farmers and creating attentiveness of the importance of the adoption of technologies enhancing the productivity of the dairy farm. According to (Howley et al., 2012) households with large family sizes could have a high probability of AI technology adoption. Lemma *et al*., (2015) in his study showed that the education status and experiences of the dairy farmers have positive and significant relationship with the adoption practices.

The study also revealed that the probability of adoption decreased with the increase in the age of household heads and increased with the level of farmers' education, farming experience, and household income (Quddus, 2013). The adoption decision of farmers is influenced by the different factors listed above. In Ethiopia, most studies show that credit, farm size, labor availability, human capital, land tenure, and education are the main factors affecting technological adoption.

2.1.8. Advantage of AI over Natural breed

Artificial insemination is a little bit of the cost of purchasing, housing, and managing a bull (Yohannes, 2014). To have improved income from livestock that supports the AI farmer to insure easily their wellbeing it is necessary to upgrade the breed of livestock. A farmer can have access, relatively inexpensively, to a wide variety of bulls without having to purchase the bulls themselves, which can cost tens of thousands of birr, and without having to care for this wide selection of bulls for a lifetime (Yohannes, 2014).

According to the University of Florida's Institute of Food and Agricultural Sciences (IFAS), a bull can be bred naturally less than 100 times per year. However, with artificial insemination, the same bull can be bred to tens of thousands of cows. Also, male animals are often more strong, powerful, and potentially ill-mannered and thus require special housing and handling equipment as mentioned, male animals can become large and aggressive (John, 2008) as cited by (Yohannes, 2014).

For high-quality bulls, semen can be collected and stored to be used for future generations, even after the bull has passed away. The risks of cattle diseases which can be spread through sexual contact are minimized with artificial insemination; because the semen of the donating bulls is tested, and the procedure itself is performed without physical contact. In addition, because the cow and bull are not in the same physical space during breeding, the chance of injury to either animal from the other is eliminated (Azage et al., 2012).

2.1.9. Economic Importance of Artificial Insemination

Several kinds of literature have been stating that improving dairy productivity plays an important role in the economic, social, and cultural status of rural households and its contribution to improving the wellbeing of the farm family (Elisa *et al*., 2015). Livestock helps with food supply, family nutrition, family income, asset savings, soil productivity, livelihoods, transport, agricultural traction, agricultural diversification and sustainable agricultural production, family and community employment, ritual purposes, and social status (MOYO *et al*., 2010).

Adopting AI plays an important role to increase the yielding capacity of cows and is the appropriate and cheapest way of genetic improvement (Kefena *et al*., 2011). It provides economical means for livestock growers to breed their males having very desirable traits and reduce the cost of keeping bulls during AI.

The widespread application of AI in countries such as the USA has resulted in a steady improvement in the genetic quality of dairy cow and a doubling of milk yields during the past 30 years (Khanal, 2010). In countries such as India, state governments were able to support AI breeding programs with the semen of exotic breeds like Holstein–Friesian, Brown Swiss, and Jersey (Gordon, 2004).

Role of Artificial insemination on Employment: According to Elisa et al., (2015), 12 to 14 percent of the world population (an estimated 750 to 900 million people) lives on dairy farms or within dairy farming households. Employment and income from dairy will vary, between and within production systems because of differences such as feed sources, management systems herd sizes, a form of milk disposal patterns, and access to or use of technology. In Ethiopia, traditional smallholder mixed farming systems generate several times more employment but low income per unit of milk produced compared with urban and peri-urban dairy systems because of the low productivity of animals in the former (Yilma et al., 2011).

(Hail, 2009) estimated that labor used in various dairy processing and marketing activities in different production systems and scales of operation in Ethiopia totaled an equivalent of 174, 000 full-time jobs in 2004. (Staal et al., 1998), reported that the urban/peri-urban system creates annually 4.4 million person days of work or 16,400 full-time jobs, while the small-scale mixed farming systems create 166 million person days of work. The production of one million liters of milk per year on small-scale dairy farms creates approximately 200 on-farm jobs. In 2010, dairying created an estimated 588, 000 full-time on-farm jobs in the country (Hemme T. and Otte, J., 2010).

2.1.10. Artificial cattle insemination in Yem Special District

Livestock is the mainstay of the livelihood of the majority of the woreda population by giving draft power supply for crop production and transport, as a source of meat, milk, yogurt, and source of cash income. Despite the all-around advantage of livestock in the woreda, productivity has remained very low because the sector is lacking adequate attention to be supported by appropriate dairy technologies.

Generally, the special district is one of those areas where backyard livestock management with traditional husbandry system. Moreover, the lack of organized and documented data on the knowledge, attitude, and practices of farmers on the livestock management system is another challenge that hinders the productivity of the sector. According to (Yohannes, 2014), adopting dairy technology had a significant effect on livestock productivity that postivily support household income generation.

The highest income was obtained from improved cattle breeds and better management systems and the lowest one was from a local breed with a traditional management system (Dehinenet et al.,2014). Adopting dairy technologies, and a better management system is to maximize the productivity of the sector.

According to the Yem special district animal production and development office and WOFED report (2019), AI technology was introduced in 2006 to the district and it was first applied to selected few farm households. Subsequently, Yem special district animal production and development office continued to widen the adoption of artificial insemination technology.

Since 2006 both artificial cattle inseminations with estrus synchronization and without estrus synchronization become practical by smallholders in the district to increase the productive performance of the sector to scale up the income of the farmer to support the wellbeing of the adopter households. Albeit such interventions, the intensity and extent of adoption of artificial insemination technology in the district are still low and it is dominated by local breed and traditional livestock management systems.

However, nowadays issues like the topographic features of the district others have initiated the farmers to focus on livestock as the first option for their livelihoods and increasing the adoption level of artificial insemination technology. Even though artificial cattle insemination is introduced to improve the productive performance of the dairy cow and to improve the well-being of the user households by generating better income from the sector its role in the household wellbeing of the user is not supported by evidence, or the economic impact of adopting artificial insemination on the well-being of the farmer is not evaluated in the district.

Moreover, recognizing the knowledge, attitude, and practices of farmers on artificial insemination technology adoption and identifying factors affecting the adoption practics are issues currently seeking research in the area.

2.2. Review of empirical studies

Several empirical studies have been conducted on the determinant factors that affect dairy technology adoption at the household level. In most studies, households' decision to adopt technology has been determined by demographic profile, personal perception, socio-economic, psychological, and institutional factors. Thus, in this section, the emphasis is given to the review of empirical literature related to farm characteristics, institutional factors, situational and farmers' perceptions towards attributes of dairy technologies, especially artificial insemination technology.

Consequently, the researcher reviewed various studies (for example (Atnafe et al., 2018); (Tefera et al., 2014) ; (Doss, C. R., 2003) and (Khanal, 2010) that principally center on households demographic characteristics such as sex, age, educational level, economic factors off-farm income, on-farm income; institutional factors, situational factors, factors related to communication and factors like being role models were important factors influencing households' decisions to adopt new technologies.

A study conducted by (Quddus, M.A., 2012) in Bangladesh confirmed that the adoption of dairy farming technologies by small farm holders particularly AI for cattle breeds, the age of the farmer was negatively related with AI technology adoption. The reason behind this can be due that with the age a farmer becomes inactive in participating the technology issues or becoming risk-averse to new technologies. This suggests that the rate of AI adoption decreases as farmers get older.

Howley *et al*., (2012), research finding shows that a household that has a large family size can have a high probability of dairy technology adoption, and farmers with children are much more likely to use breeding services. This shows family size and adoption status of the AI technology was robustly and positively related.

In addition, it was found that household head education status significantly affects the adoption of artificial insemination technology positively. This implies that better educated household heads are in a position to understand and interpret what ever technology easily and implement own farms. According to Paulos *et al.*, (2004) education is very vital to adopting new technology and it improves the readiness of farmers to accept new technologies. In addition to this, it increases the willingness of the farmers to adopt AI technology and helps to decide.

Study by Yohannes, (2014), coorporating with the study by Tefera and Gebre, (2015) have stated that other factors like knowledge about improved livestock breed practices like knowledge of heat detection, timely availability of the technology, perception of the importance of AI service, and access to grazing land indicated a positive relationship with the adoption of these technologies.

A study conducted in Brazil on the impact of AI by Ferraz et al., (2012) as cited by (Yohannes, 2014), revealed that direct and indirect impacts of increasing AI adoption and genetically superior replacement bull's utilization show that the value of these actions is remarkable. According to Ferraz et al., (2012), any increase in the use of genetically superior animals will cause very significant economic effects in the Brazilian beef industry, reaching values as high as US$ 342 million with only 200% of increment which, with the fast growth of AI, is going to be reached in near future.

A study conducted in India (Singh, 2013) shows distance from AI center has a negative influence on the adoption of dairy technologies. It shows that the message communicated to the livestock owners had more impact on those livestock owners who are situated beyond the 5 km radius of the AI center as compared to those who are situated within a 5 km radius. This means, distance from the artificial insemination service to the farmers home has a negative and significant impact on probability of the household adoption for technology by decreasing the accessibility of farmers for such technology (Quddus, 2013).

As indicated in the study of (Dehinenet *et al.*, 2014), it is confirmed that there is a difference between dairy technology adopters and non-adopter in terms of production and productivity that can bring a different well-being status between the user and non-user households. AI user households could get more milk income on average than non-users and could have better household well-being.

Various cross-country studies have revealed that higher income, nutritional security and improved well-being effect of commercial dairy farming that results from the adoption of artificial insemination technology. For instant, studies carried out by Alary et al. (2011) in Niger, Mali; Melesse and Jemal, (2013) in Ada's and Lume districts of Central Ethiopia; Quddus (2012) in Bangladesh; Udo and Steenstra (2010) in Indonesia, etc. have found a positive impact of AI technology adoption on income and household wellbeing of dairy farm households. Adoption of artificial insemination technology can be a suitable opportunity for improving farmers' wellbeing through enhancement of livestock income.

A study by (Valergakis et al, 2007), indicates that daughters of AI sires were producing almost 900 kg of extra milk per lactation than daughters of natural service bulls. Another report from the USA showed a difference of more than 1000 kg of milk per lactation on farms using AI (Smith et al., 2005) and (Temesgen et al., 2017). This means using AI can be more profitable (Valergakis et al, 2007). Using AI for cattle breeding plays an important role in enhancing animal productivity, especially milk yields, in developing countries that have a well-defined breeding strategy and a sound technical base to absorb and adapt the technology to meet their needs and get better welfare (BBC, 2015).

2.3. Literature gap

From the above theoretical and empirical literature reviewed, it can be understood that most of the studies focused on either identifying the importance of using AI for improving livestock breed or discussing the way of adopting artificial insemination; but none of them have identified and evaluated the impact of adopting artificial insemination on the well-being of user households. Also, the intensity or the extent of the adoption is not identified. So this study has designed to examine the economic impact of adopting AI on the well-being of users' household and identify the factors that determine the adoption participation and intensity of adoption in the study area. Through these, it was intended to contribute and fill the knowledge gap regarding its impact on household well-being and the adoption practics

2.4. Definitions and Approaches of Impact Assessment

Different definitions have been given to impact assessment by different organizations and scholars. But the commonly used definition of impact assessment as it is given by Omoto (2003) and Rover and Dixon (2007), is that it is a process of systematic and objective identification of the short and long-term effects–positive and negative, direct or indirect effect of intervention on economic, social, institutional and environments. Such effects may be anticipated or unanticipated, and positive or negative, at the level of the individual, household or the organization caused by on-going or completed development activities such as a project or program.

2.4.1. Approaches to impact assessment study

2.4.1.1. Experimental Method

Experimental designs, also known as randomization, are generally considered as the most robust of the evaluation methodologies (Baker,2018). In a randomized experiment, individuals are randomly placed into two groups, namely, those that receive treatment and those that do not. In this case observable and unobservable characteristics get uncorrelated thus no selection bias problem arises (Nssah, 2006).

Although experimental designs are considered the optimum approach to estimate project/program impact, in practice, there are several problems. It is not feasible in demand driven programs in which participants make their own decisions of whether to participate and about the kind of activities to do in the learning process (Bernard T., and Alemayehu 2010). Moreover, experimental designs can be expensive and time consuming in certain situations, particularly in the collection of new or raw data.

2.4.1.2. Quasi-experimental method

Quasi-experimental (nonrandom) methods can be used to carry out an evaluation when it is not possible to construct treatment and comparison groups through experimental design. For projects that are often setup intentionally, it is common to only have access to a single cross-sectional survey done after the project is introduced (Ravallion, and Jalan, 2005). A quasi-experimental method is the only alternative when neither a baseline survey nor randomizations are feasible options (Ravallion, and Jalan, 2005).

The principal disadvantages of quasi-experimental techniques are that (a) the reliability of the results is often reduced as the methodology is less robust statistically; (b) the methods can be statistically complex and data demanding; and (c) there is a problem of selection bias.

Double difference or difference-in-differences (DID): The difference-in-difference used when baseline and time series information on both participants and non-participants is available (Stern et al., 2012). Method in which one compares a treatment and comparison group (first difference) before and after a project (second difference). The DD estimate of impact can be written as follows:

$$\mathrm{DD} = (Y_{Treatment\ after-}\ Y_{Treatment\ before}) - (Y_{Control\ After-} Y_{control\ before})$$

However, there are at least two disadvantages that relate to the very simplicity of such a panel based impact assessment. First, constructing panel data sets can be expensive, time consuming, and logistically challenging particularly because we need to collect baseline and follow-up data that straddle the implementation of a program. Second, the design assumes that the potential selection bias(i.e., due to administrative targeting or volunteering) is linear and time invariant such that it can be subtracted off in the first differencing (Van de, et al., 2013).

Instrumental variable(IV): The method uses the change in outcomes induced by the change in participation rates to estimate program impacts. The instrument affects participation in the program but does not directly affect outcomes (that is, the instrument affects outcomes only by changing the probability of participating in the program).

Regression discontinuity design(RD):. There is a cutoff that determines whether or not a unit is eligible to participate in a program. Outcomes for participants on one side of the cutoff are compared with outcomes for nonparticipants on the other side of the cutoff. Units that are close to the cutoff but are ineligible to receive the program. To identify unbiased program impacts for the population close to the cutoff, units that are immediately below and immediately above the cutoff are statistically identical.

Propensity Score Matching (PSM): Among quasi-experimental design techniques, matched comparison techniques are generally considered a second-best alternative to experimental design Baker, (2018), it is the conditional probability (P(X)) that is intended to be uniform between participants and matched comparators, while randomization assures that the participant and comparison groups are identical in terms of the distribution of all characteristics whether observed or not.

Matching the treated and the control subjects becomes difficult when there is a multidimensional vector of characteristics (Rosenbaum and Rubin, 1983). The PSM solves this type of problem by summarizing the pre-treatment characteristics of each subject into a single index variable, and then using the propensity score (PS) to match similar individuals.

Propensity Score Matching is extensively used in the recent literature on economic impact evaluation (Ravallion, and Jalan, 2005). It is very appealing to evaluators with time constraints and working without the benefit of baseline data given that it can be used with a single cross-section of data, where this study envisaged to employ.

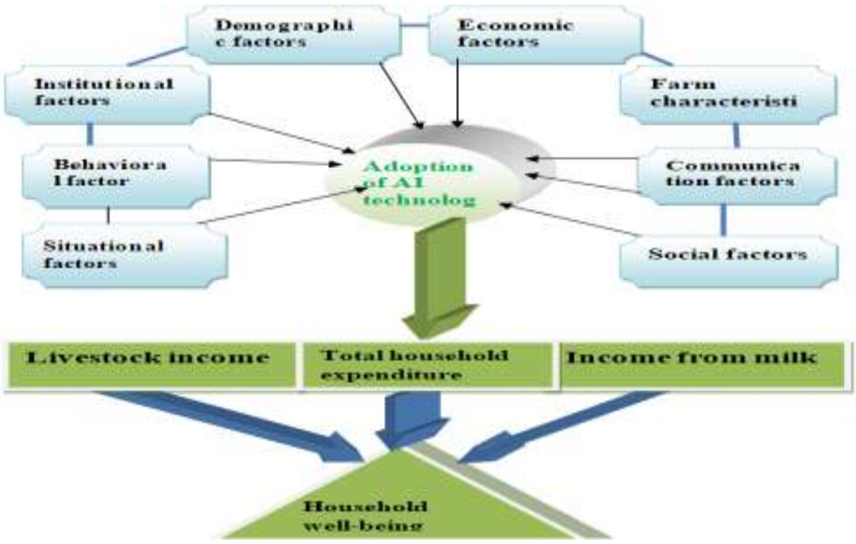
2.5. Conceptual Framework

The adoption of artificial insemination for cattle breeding has a tremendous influence on the well-being of farm households. The findings of different studies conducted on the adoption of artificial insemination in different parts of the world indicate that improving the productive performance of livestock; especially small-scale dairy holders can affect their household well-being significantly.

The framework is designed based on the reading of various kinds of literature related to AI technology adoption in different times and places. It holds the main factors that determine the adoption of AI technology by rural households and the extent of the adoption. These are behavioral, economic, situational, communication, institutional, farm characteristics, social factors, and demographic profiles. Socioeconomic factors related to social activities and capital of farmers like farm and non-farm income, and farming experience. The other major factors of household adoption of technologies are institutional and situational. Such factors include timeliness of the service, knowledge of heat detection and distance from the AI center to the farmer's home are the major factors farmers faced on the institutional and situational side. The last one is demographic factors like the education level; the age and sex of the household head and family size also have a big role in the adoption process of rural households. Different countries revealed that demographic, socioeconomic, and institutions affect the adoption of improved cattle breeding technologies.

Figure (1); illustrate the effect of demographic, behavioral, economic, situational, communication, and institutional as well as the farm characteristics and social factors on the usage of AI service. In this study, the mentioned factors were hypothesized and thirteen variables are addressed. These are age, sex, educational level and family size of the household head, timeliness of the service, perception about the importance of AI service, knowledge of heat detection, having mobile phone, access to grazing land, distance from AI service, non-farm and farm income of the household head was included in the study.

Figure 1: Conceptual Framework of the study



(Source: own computed)

CHAPTER THREE

RESEARCH METHODOLOGY

This section presents the methodological approach to the study as well as the methods employed in data collection. The section begins by describing the study area and research design, followed by the sampling technique and sample size determination, discussing source and types of data, data collection techniques as well as the method of data analysis.

3.1. Dsription of the study area

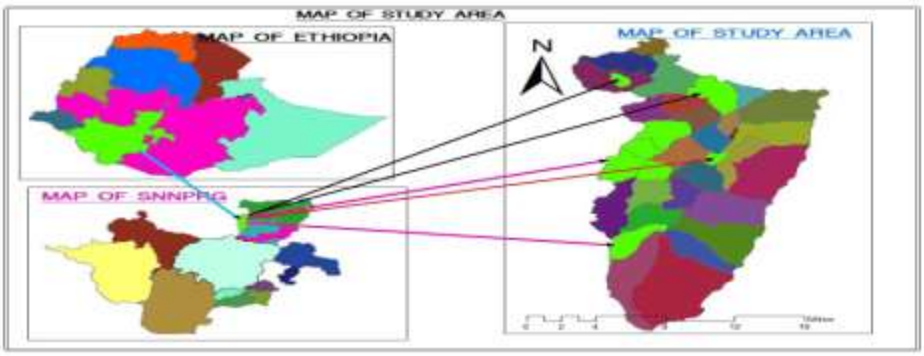
The study was conducted in Yem special district, located in the north-western apex of the Southern Nations, Nationalities, and Peoples Regional State of Ethiopia. The administrative center of Yem special woreda (saja) is located 247 km from Addis Ababa Southwest Ethiopia. Yem is bordered on the west and north by the Oromia Region and separated from Gurage on the northeast and Hadiya on the east by the gibe River. Yem occupies a surface area of 724.5 km2. The woreda lies within elevations of 920–2939 meters above sea level (MASL) and has three traditional agro-climatic zones; namely, Dega (cool highlands) 18.4%, Weyna Dega (tropical highlands) 57.6%, and Kolla (lowlands) 24.0%. It receives a mean annual rainfall of 900 – 2200 mm in a bimodal pattern, from mid-February to April, and from June to September. The mean annual temperature is in the range of 12– 30°C (IEP, 2010).

The topography of the Special district is characterized by rolling mountains, long gorges, steep slopes, and flat to undulating plateaus. The physiographic features of the woreda are characterized by high peaks, and mountains and partly by deep gorges of Gibe River to the east (IEP, 2010). The total human population of the woreda as per the 2007 population census is estimated to be 80,647 of which 50.3% are male and 49.7% female (CSA, 2010/2011) and the population density is 111.3 persons/km2. The major livestock production system in the woreda is cattle in Mixed crop-livestock farming and it comprise more than 43.7% (n= 107,201) of the regional livestock population (USAID, 2005).

The three most numerous ethnic groups reported in this woreda were the Yem (90.57%), the Oromo (5.41%), and the Hadiya (1.27%); all other ethnic groups made up 2.75% of the population. Yemsa is spoken as a first language by 72.67% of the inhabitants, 22.63% speaks Oromiffa, 2.57% speak Amharic, and 1.16% speaks Hadiya; the remaining 0.97% speaks all other primary languages reported. 63.05% of the population practiced Ethiopian Orthodox Christianity, 27.09% were Muslim, and 9.61% were Protestants (CSA /Central Statistical Agency, 2010/2011). Rain-fed agriculture is a common practice in the district, the dominant crops being cereals and enset. Enset is the main staple; the full set of annual field crops cultivated includes wheat, barley, teff, maize, sorghum, and bean (USAID, 2005).

Different economic indicators are related to farming and non-farming activities in the districts. Farming activities like the production of cash crops and cereal crops and also non-farm activities like working for wage, handcrafts, petty trading, livestock (like dairy cattle production), livestock trade, production of fuel-saving stoves, and sale of firewood and charcoal are common. Livestock is the mainstay of the livelihood of the majority of the woreda population by giving draft power supply for crop production and transport, as the source of meat, milk, egg, and source of cash income. Despite their all-around advantage of livestock in the woreda, productivity has remained very low. To promote the productivity of the sector currently, artificial insemination technology becomes adopted by smallholders in the district. However, its impact on their well-being is not evaluated. Finally, these points become one of the motives that the researcher is interested to conduct his study in this area and finding a solution.

Figure 2: Administrative map of Yem Special District



(Source: Yem Special district agriculture office)

3.2. Research Design

The study applies cross-sectional survey methods that both qualitative and quantitative design were employed to address the proposed study objectives. Quantitative methods aim to classify features, count them, and create statistical models to test hypotheses and explain observations, interviews, and the use of questionnaires. Qualitative methods aim for a complete, detailed description of observations, including the context of events and circumstances.

3. 3. Target Population

The target population of this study was artificial insemination technology-adopting households in selected kebeles of Yem special Woreda southern Ethiopia.

3.4. Sampling technique and sample size determination

Determining the sample size is a credible issue, because a sample that is too large may be a waste of time and resources, while a sample too small may lead to inaccurate results, so determining the sample size is the imperative step in the overall economical and statistical process. An appropriate sample size is a means of gaining high precision, accuracy, and cost-effectiveness.

According to the data obtained from Yem special woreda agriculture office, there are 32 rural kebeles and 5 urban centers in the woreda. Among 37 total kebeles, 25 kebeles are using artificial insemination technology. The two-stage sampling procedure was employed in this specific study. In the first stage, the 8 representative kebeles were selected purposively from 25 AI adopting kebeles based on the number of adopters in the kebele. The researcher has selected the first 8 potential adoptive kebeles. These sample kebeles are Fofa ketem, Saja ketema, layigna kesheli, tachi kesheli, Nubba, Gessi, Tobba ketem and Deri tegu kebele). Secondly, within the 8 kebeles, the respondent households were stratified into two groups: adopters and non-adopters. In the end, simple random sampling was applied to select the sample households from the two strata. A total of 361 sample households were selected and out of which 117 were adopters and 244 were non-adopter households.

The sample of the respondent households was selected representative way of selection with a ±5% precision level and 95% confidence interval. The main reason is to get enough matches that enabled us to reach research objectives. To determine respective sample households of 8 kebeles for each stratum, selected by using probability proportional to the size of households. Finally, a representative sample for each stratum was selected by using probability proportional to size applied across each category. As to Kothari, the following statistical sample size decision formula for household size (N) that is less than or equal to 10,000 was used. Then the sample size is determined by using Kothari's (2004) formula as represented in equation (1).

$$n_0 = \frac{Z^2 pq}{e^2} \qquad (1)$$

Where,

n = the desired sample size; Z= is the abscissa of the normal curve that cuts off an area α at the tails ($1 - \alpha$ equals the desired confidence level, 1.96 for 95%);

e = is the desired level of precision $\pm$ 5%, p = is the estimated proportion of an attribute that is present in the population, and q is 1-p.

$$n_0 = \frac{(1.96)^2(0.5)(0.5)}{(0.05)^2} = 385$$

$$n = \frac{n_0}{1+\frac{(n_0-1)}{N}}$$

$$n = \frac{385}{1+\frac{(385-1)}{5769}} = 361$$

Table 1: Distribution of sample respondent probability proportional to size

Kebeles Name	Total HHs in each Kebele	Adopter HH		Non-adopter HH		Total Sample selected HH
		Total	Sample	Total	sample	
Fofa	1138	330	21	808	50	71
Tachi kesheli	969	284	19	685	42	61
Saja	1018	261	18	757	46	64
Gesi	879	257	16	622	39	55
Laye Kesheli	451	174	11	277	17	28
Toba ketema	458	166	11	292	18	29
Nuba kebele	515	182	12	333	20	32
Deri tegu	341	137	9	204	12	21
Total	5769	1791	117	3978	244	361

Source: Computed based on data from Yem Special woreda Agriculture Office.

3.5. Source and Types of Data

Both qualitative and quantitative data from primary and secondary sources were used in this study. The primary data was collected from sampled households, AI technicians, Woreda agricultural offices, and site development agents (DA). The structured questionnaire was filled by respondents, focus group discussion with farmer groups who were selected purposively, and an in-depth interview was conducted to collect the primary data. On the other hand, qualitative data type was collected through focus group discussion and key informant discussions with kebele administrators and personal observations. Secondary data were collected from records of the woreda agricultural offices, and other related data prepared by the government and non-governmental organizations. The questionnaire includes information on household demographic characteristics, socioeconomic and institutional, behavioral, situational, social, and communication factors related information.

3.6. Data Collection Techniques

Primary data was collected from the household survey, key informant discussion, structured interview, and focusing group discussion. While secondary data is collected from published and unpublished works related to AI technology.

3.6.1. Household survey

The household survey was conducted using a structured questionnaire. The questionnaire was translated into Amharic for simplicity of communication between enumerators and respondents. Data collectors were oriented on issues related to data collection procedures and ethics. A pilot study was undertaken before full-scale data collection for pre-testing the questionnaire to estimate the time needed to complete and implement it. With this technique data related to socio-economic, institutional, situational, behavioral, and demographic features that are listed in the explanatory variable include the determinant factors that affect the adoption decision of households, the extent or the intensity of the adoption as well as the impacts of AI technology on small householder’s well-being.

3.6.2. Focus Group Discussion (FGD)

Focusing group discussion was carried out with purposively selected six individuals from each group and each sample kebele, and agricultural extensions to collect opinion, qualitative and quantitative descriptions about the AI adoption status, and the factors that influenced the adoption of the technology as well as the impacts of adoption on household well-being. Every selected kebeles has one FG group with purposively selected six individuals from adopters and six from non-adopters.

3.6.3. Key Informant Interview (KII)

Key informant interview was carried out to collect required primary data that lead to a discussion with concerned bodies to obtain information about the issue related to the study objectives. The key informants of this particular study were woreda agriculture office directors, woreda livestock experts, cluster level AI technicians, and kebele level development agents. The interview was recorded using a checklist.

3.6.4. Observation

The field observation was carried out for validation and triangulation of the information provided through primary and secondary data collection tools. As well as information like socioeconomic, situational, and individual farm characteristic conditions of the study area were explored through field visits.

3.6.5. Secondary data

Concerning secondary sources, data was collected from a review of different documents including research works, office documents like woreda agricultural and natural resource office, journals, articles, and reports that had been written by different scholars on related issues. Documents from various official websites such as; the Ministry of Agriculture, National Artificial Insemination Center (NAIC), World Bank (WB), Dairy Development Agency (DDA), International Livestock Research Institute (ILRI), Minister of Agriculture and Natural Resource (MoANR), Ethiopian Institute of Agricultural Research (EIAR), Central Statistical Agency (CSA), National Metrological Agency (NMA) were reviewed.

3.7. Methods of Data Analysis

Data analysis is the critical part of the study by which the researcher would extract information from collected data. It provides the researcher with the process of investigating questions. The process of data analysis includes steps like categorization, coding, statistically adjusting the data, and tabulation. The quantitative data analysis involves descriptive statistics such as mean, standard deviation percentage, and frequency distribution. Inferential statistics such as the chi-square test (for categorical variables and F-score and/or t-test (for continuous variables) were applied. The binary logistic regression model, Tobit model, and Propensity Score Matching (PSM) method were used in this study. The model helped to describe the relationship between the outcome variable and a set of explanatory variables as well as the impacts of artificial insemination technology on household well-being respectively. Finally, software STATA-13 and excel were employed for both descriptive and empirical analysis.

3.7.1. Descriptive statistics

Descriptive statistics describe the basic features of the data. It provide simple summaries of the sample and the measures. Together with simple graphics analysis, they form the basis of virtually every quantitative analysis of data. Descriptive statistics describe the data using mean, standard deviation, percentages, graphs, and t-tests.

3.7.2. Propensity Score Matching Method (PSM)

The propensity score matching method with the logit model was used to address the impact of adopting AI on smallholder farmers' well-being. One of the critical problems in non-experimental methods is the presence of selection bias which could arise mainly from the non-random location of the AI technology and the nonrandom selection of participant households that makes evaluation problematic (Heckman *et al*., 1998).

Bernard *et al*., (2010), there are three potential sources of bias. The first one is that participant households may significantly differ from nonparticipants in the community as well as household level due to observable characteristics (such as geographic remoteness, or a household's physical and human capital stock) that may have a direct effect on the outcome of interest. Secondly, the difference arises due to unobservable community-level characteristics. Thirdly, externalities (spillover effect) are exerted by the technology adopter on non-adopters. As a result of these problems, differences between participants and non-participants may, either totally or partially, reflect initial differences between the two groups rather than the effects of adopting artificial insemination.

PSM method controls the households' observable characteristics by comparing the outcomes of adopters of AI with those of matched non-adopters, based on similarity in observed characteristics which minimizes the first bias. If not feasible to control for these characteristics, PSM estimation becomes biased. Having control households from the same communities as beneficiaries of the AI service helps to reduce the risks of such bias. However, removing unobservable characteristics remains the main problem of this method. (Bernard *et al*., 2010), claim to have minimized the effect of spillover effect on the comparison group by comparing cooperative members to similar households located in other kebeles where there are no cooperatives. Nevertheless, as argued by (Heckman *et al*., 1998), treatment and comparison households should operate in the same environment and should have come from similar agroecology (from sufficiently close locations) and socio-economic conditions to ensure the validity of the PSM method.

(Caliendo and kopeinig, 2005), the implementation of PSM involves five steps. These are PSM estimation, choosing a matching algorithm, checking for sufficient overlap (common support), estimating the treatment effect and assessing matching quality, and finally sensitivity analysis. To attain the intended objectives, PSM non-experimental method was employed to know the impact of adopting artificial insemination on outcome variables. It is preferred among other non-experimental methods because it does not require baseline data, the treatment assignment is not random, and considered the second-best alternative to experimental design in minimizing selection biases (Baker, 2000).

3.7.3. Mathematical Specifications of PSM Method

Estimating the effect of adopting AI on a given outcome (Y) is specified as:

$Ti = Yi\ (Di = 1) - Yi\ (Di = 0$ .... (2)

Where Ti is the treatment effect (effect of using AI), Yi is the outcome on household **i**, Di is whether a household **i** has got the treatment or not (i.e., whether a household use AI service for breeding cows or not).

However, one should notice that Y (Di = 1) and Y (Di = 0) cannot be observed for the same household at the same time simultaneously. Due to this fact, estimating individual treatment effect **Ti** is not possible and one has to shift to the average treatment effects of the population than the individual one. Two treatment effects are most frequently estimated in empirical studies. The first one is the (household) Average Treatment Effect (ATE), which is simply the difference in the expected outcomes by considering users and non-users specified as:

$TATT = E(T \mid D = 1) = E\ [Y_1 \mid D = 1] - E\ [Y_0 \mid D = 1]$... (3)

This answers the question, how much did households participating in the program benefit compared to what they would have experienced without participating in the program? Since the counterfactual mean for those being treated, E[Y (0) D =1] is not observed, there is a need to choose a proper substitute for it to estimate ATT. Though it might be thought that using the mean outcome of the untreated individuals [Y (0) D = 0] as a substitute to the counterfactual mean for those being treated, E[Y (0) D =1] is possible, it is not a good idea, especially in non-experimental studies. This is because it is likely that components that determine the treatment decision also determine the outcome variable of interest.

In our variables adopting AI affects a household's well-being. Therefore, the outcome of individual households from both groups would differ even in the absence of treatment leading to a self-selection bias. However, by rearranging and subtracting E[Y (0) D = 0] from both sides of equation 3, ATT can be specified as;

$$E\,[Y_1 \mid D = 1] - E\,[Y_0 \mid D = 0] = TATT + E\,[Y_0 \mid D = 1] - E\,[Y_0 \mid D = 0] \;\ldots\ldots\ldots\; (4)$$

In equation (4) both terms on the left-hand side are observables and ATT can be identified, if and only if $E[Y1|D=1]-E[Y0|D=0]=0$. i.e., when there is no self-selection bias. This condition can be insured only in social experiments where treatments are assigned to units randomly (when there is no self-selection bias). In non-experimental studies, one has to introduce some identifying assumptions to solve the selection problem. The following two assumptions to solve the selection problem.

I. **Conditional Independence Assumption (CIA):** The CIA is given as

$$\mathbf{Y}_{\mathbf{1}} \perp D / X, \forall X \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Where $\perp$ indicates independence;

X = is a set of observable characteristics

$\mathbf{Y}_{\mathbf{0}}$ = control household and

$\mathbf{Y}_{\mathbf{1}}$ = treated household

Given a set of observable covariates (x) which are not affected by treatment (in our case, using AI), potential outcomes (well-being) are independent of treatment assignment (independent of how households decide to use AI). This assumption implies that the selection is solely based on observable characteristics (x), and variables that influence treatment assignment (decision to implement artificial insemination is made by the household) and potential outcomes (household well-being) are simultaneously observed (Caliendo and Kopeinig, 2008). Hence, after adjusting for observable differences, the mean of the potential outcome is the same for D =1 and D =0 and $E\,(Y0 \mid D = 1, X) = E\,(Y0 \mid D = 0, X)$.

The PS is defined as the probability of participation for household i was given a set of households' characteristics $P(x) = pr\ (D=1 \mid X)$. Propensity scores are derived from the discrete choice model and then used to construct the comparison groups.

Matching the probability of participation, given covariates solves the problem of selection bias using PSM (Liebenehm *et al*, 2009). The distribution of observables is the same for both users and non-users given that the propensity score is a balancing score (Liebenehm *et al*., 2009). If outcomes without the intervention are independent of participation given then they are also independent of participation given X. This reduces a multidimensional matching problem to a single-dimensional problem. Due to this, differences between the two groups are reduced to only the attribute of treatment assignment, and an unbiased impact estimate can be produced (Rosenbaum & Rubin,1983).

II. Common support region assumption

The common support is the region where the balancing score has a positive density for both treatment and comparison units. This assumption rules out perfect predictability of D given that $0 < pr\ (D = 1 \mid X) < 1$.

This assumption improves the quality of the matches as it excludes the tails of the distribution of X though this is done at the cost that the sample may be considerably reduced. Yet, non-parametric matching methods can only be meaningfully applied over regions of overlapping support. No matches can be formed to estimate the parameters when there is no overlap between the treatment and comparison groups. It also guarantees an individual with observable characteristics has a positive probability of belonging both to the participants and control group (Rosenbaum and Rubin, 1983). Given the above assumptions, the PSM estimator of ATT can be written as:

$$TATT = E\ [Y1–Y0 \mid D=0, p\ (x)] =E\ [(Y1D =1, p(x)] - E\ [(Y0 \mid D = 0, p(x)] \ldots (6)$$

Where p(x) is the propensity score computed on the covariates X. Equation (6) is explained as; the PSM estimator of the mean difference in outcomes over the common support, appropriately weighted by the propensity score distribution of participants. According to (Caliendo and Kopeinig, 2008), there are steps to implementing PSM. These are an estimation of the propensity scores using a binary model, choosing a matching algorithm, checking on common support conditions, and testing the matching quality.

3.7.4. Estimating propensity score using binary response model

First, the propensity score can be obtained using either logit or probit models to predict the probability of using artificial cattle insemination. According to (Gujarati,2004), both provide similar results. Thus, for comparative computational simplicity logit model will be used to estimate propensity scores using households' pre-intervention characteristics (Rosenbaum and Rubin, 1983), and matching is then performed using propensity scores of each observable characteristic, which must be unaffected by the intervention.

A dependent variable (using AI), Y, is a binary variable taking the value 1 indicating participation in artificial insemination adoption and 0 otherwise. Since Y is binary the error term in the model is also binary. The independent variables (sex, age, family size, education level, land size, having a mobile phone, knowledge of heat detection, off-farm income, farm income, timeliness of AI service, perception, and distance to the AI center) are used to measure the probability of the variable in this research.

Assessing the impact of an intervention requires making an inference about the outcomes that have been observed and had not been observed (counterfactual). Here an ideal comparison group from the study will be created. The comparison group is matched to the treated group based on a set of observed characteristics or using the predicted probability of participation given observed characteristics (propensity score). A good comparison comes from the same economic environment as the treatment group and is administered using the same questionnaire.

Logit model:

$$L_i = \ln\{(P_i/1 - P_i)\} = \beta_0 + \beta_1 X_i + \mu_i$$

Where, $L_i = \ln(1)$, if a participant (AI adopter)

$L_i = \ln(0)$, if a not- participant (not AI adopter)

Pi = 1, if participant, Pi $= 0$, if not participant, Xi= independent variables.

βi = Coefficients,i=1,2,3,... = n, and n is the number of independent variables.

μ= Error term.

Rosenbaum and Rubin (1983) revealed that matching can be performed conditioning only on P(X) rather than on X, where P(X) = Pr (D=1|X) is the probability of participating in the program conditional on X. According to these authors, if outcomes without the intervention are independent of participation given X, then they are also independent of participation given P(X) which reduces a multidimensional matching problem to a single dimensional problem. Regarding the decision of choosing the type of model to be used, for the binary treatment case, where we estimate the probability of artificial cattle insemination adopter and non-adopter household, both logit, and probit models often yield similar results. Therefore, it is not a critical problem. However, due to the complexity of the estimation procedure of the probit model than the logit model, logit is widely used (Caliendo and Kopeinig, 2008).

To capture this advantage, the logit model was used for estimating the propensity score in this study. Regarding the choice of what variables should be included in the model, a matching strategy should be built on the conditional independence assumption (CIA) that requires the outcome variables must be independent of treatment conditional on the propensity score.

Therefore, implementing matching is based on choosing a set of variables X covariates) that reasonably satisfies this condition (Caliendo and Kopeinig, 2008). Economic theories, better knowledge of previous research, and information on institutional settings are important guides to selecting appropriate covariates (Sianes, 2003); (Smith and Todd, 2005).

(Gujarati,2004), in estimating the logit model, the dependent variable is adopting cattle artificial insemination which takes a value of 1 if the household is using AI and 0 otherwise. The logit model is mathematically formulated as follows:

$$pi = \frac{e^{zi}}{1+e^{zi}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(7)}$$

Where P_i is the probability of participation for the i^{th} household & it ranges from 0-1.

Zi: is a function of n-explanatory variables which is also expressed as:

$$Zi = \beta o + \sum \beta iXi + \cup i \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(8)}$$

Where, i = 1, 2, 3, ----, n.

Where, $\beta 0 = \text{intercept}$

$\beta i = \text{regression coefficients to be estimated or logit parameter.}$

$ui = \text{a disturbance term, and}$

$Xi = \text{pre} - \text{intervention characteristicsd}$

The probability that a household belongs to non participant is:

$$1 - pi = \frac{1}{1+e^{zi}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(9)}$$

Then the odds ratio can be written as:

$$\frac{Pi}{1+Pi} = \frac{1+e^{Zi}}{1+e^{-Zi}} = e^{Zi} \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(10)}$$

The left-hand side of equation (10) is simply the odds ratio in favor of AI using household. It is the ratio of the probability that the household would participate to the probability that he/she would not participate. Finally, by taking the natural log of equation (10) the log of odds ratio can be written as:

$$Li = Ln(\frac{Pi}{1-Pi}) = Ln(e^{\beta 0+\sum_j^n=1^{\beta}j^{X_{ji}}}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(11)}$$

Where; Li is the log of the odds ratio in favor of households using AI service, which is not only linear in Xi, but also linear in the parameters.

3.7.5. Tobit model

The Tobit model measures not only the probability that farmers to adopt the new practice but also the intensity of use once they adopted the technology. Therefore, the application of the Tobit model provides the needed information on the probability and intensity of the adoption of the technology. Thus, it depends on the intensity of to use of the technology (Maddala, 1997).

3.7.6. Estimation of Tobit model

Factors affecting the extent of adoption of artificial insemination technology were analyzed using the Tobit model. Tobit, a hybrid of the Probit and multiple regressions analysis, model also called limited dependent variable regression model is censored, normal regression model. This model was used by (Ojiako et al., 2007) and (Kaaya et al., 2005) in the intensity of adoption studies. Direct application of the Tobit estimation sufficiently provides the needed information on the probability and intensity of artificial cattle insemination technology adoption.

Tobit model for the continuous variable adoption index

$AI_i = \beta 0 + \beta i Xi + Ui$

$AI_i = AI$ if $\beta 0 + \beta iXi + Ui > 0$ --------------------------------------- (12)

$A1i$ is the observed dependent variable *i.e.* the number of improved dairy cattle adopted, and βi is a Vector of parameters to be estimated.

To determine the derivates of the estimated Tobit model is to predict the effect of change in the explanatory variable. Thus, proposed the following techniques to decompose the effects of the independent variable into adoption and intensity effects (Johnston and Dandiro, 1997). It affects the conditional mean of AI in the positive part of the distribution and it affects the probability that the observation will fall apart of distribution. In this study, the marginal effect of explanatory variables was estimated as follows:

1. The marginal effect of the explanatory variable on the expected value of the dependent variable is $\frac{\partial(AIi)}{\partial \mathrm{Xi}} = F(z)\beta i$ ---------------------------------- (13)
2. The change in the probability of adopting technology as an independent variable Xi change is $\frac{\partial F(Z)}{\partial \mathrm{Xi}} = F(z)\frac{\beta i}{\sigma}$ ----------------------------- (14)
3. The change in the intensity of adoption to a change in an explanatory variable among adopters is $\frac{\partial \epsilon\left(\frac{AIi}{A1i}\right)>0}{\partial \mathrm{Xi}} = \beta i\left[1 - Z\left(\frac{f(z)}{F(z)} - \left(\frac{f(z)}{F(z)}\right)^2\right]\right.$ --------------- (15)

Where F(z) is the cumulative normal distribution of Z, f(z) is the value of the derivative of the normal curve at a given point and Z is the z-score for the area under the normal curve β is a vector of Tobit maximum likelihood estimate and σ is the standard error of the error term.

Adoption is a decision household to accept innovation (Rogers, 1983). This study measures the intensity of AI technology adoption and its applied adoption index(AI). AI= measures the extent of adoption at the time of the survey.
Accordingly, the adoption index score of 0 points implies non-adoption of AI technology, and the adoption index score of 1 implies the respondent household adopted AI practice according to the recommendation. Therefore, the actual adoption index score ranges from 0 to 1.

3.7.7. Choice of matching algorithm

Estimation of the propensity score is not enough to estimate the ATT of interest. This is because propensity score is a continuous variable and the probability of observing two units with the same propensity score is, in principle, zero. Various matching algorithms have been proposed in the literature to overcome this problem.

However, they all provide consistent estimates of the ATT under the CIA and the overlap condition (Caliendo and Kopeinig, 2008). The most commonly applied matching estimators are described below.

Nearest neighbor (NN) matching: This is the most straightforward matching estimator. The individual from the control group is chosen as a matching partner for a participant individual that is closest in terms of propensity score (Caliendo and Kopeinig, 2008). Nearest neighbor matching can be done with or without replacement. In the case of replacement, an untreated individual can serve more than once as a match, whereas it is considered only once in the case of without replacement. Nearest neighbor matching with replacement increases the average quality of matching and decreases the precision of estimation while the reverse is true in the case of without replacement (Caliendo and Kopeinig, 2008).

Caliper matching: Conducted to overcome the downsides of nearest neighbor (NN) matching risk of bad matches when the closest neighbor is far away. To eliminate this dilemma researchers use the second alternative matching algorithm called caliper matching.

Caliper matching means that an individual from the comparison group is chosen as a matching partner for a treated individual that lies within a given caliper (propensity score range) and is closest in terms of propensity score (Caliendo and Kopeinig, 2008). One problem in caliper matching is that it is difficult to know priory what choice for the tolerance level is reasonable.

Radius matching: is suggested by (Dehejia and Wahba, 2002) as an alternative to solve the drawback of caliper matching. In radius matching, the principle is to use not only the nearest neighbor within each caliper but all of the comparison members within the caliper. The advantage of this method is that it uses only as many comparison units as available within the caliper and therefore allows for the usage of extra units when good matches are not available and avoids the risk of bad matching.

Kernel and local linear matching (KM & LLM): kernel matching and local linear matching are non-parametric matching estimators that use weighted averages of all individuals in the control group to construct the counterfactual outcome and have the potential of overcoming the problems of only a few observations from the comparison group are used to construct the counterfactual outcome of a treated individual that other estimators have in common (Caliendo and Kopeinig,2008). These methods use more information and are hence advantageous in lowering variance. However, they have a drawback of the probability of using observations having bad matches which leads to the importance of imposing the common support condition (Caliendo and Kopeinig,2008).

Weighting on propensity score: Given several matching estimator algorithms, which approach is selected in the basic question? According to (Caliendo and Kopeinig, 2008) there is no best-fit algorithm for all cases. Rather the choice depends on the data in hand.

Region of common support and overlap condition: Imposing common support is the third important step in PSM because the average treatment effect on the treated and the population is only defined in the common support region. The common support region is the area within the minimum and maximum propensity scores of treated and untreated groups, respectively (Caliendo and Kopeinig,2008).

3.7.8. Testing the matching quality

Since we do not condition all covariates but the propensity score, it has to be checked if the matching process can balance the distribution of the relevant variables in both the treatment and comparison group. The main reason for the propensity score matching is not to perfectly predict selection into treatment but to balance all covariates. While differences in covariates are expected before matching, these should be avoided after matching. The primary purpose of the PSM is that it serves as a balancing method for covariates between the two groups.

Consequently, the idea behind balancing tests is to check whether the propensity score is adequately balanced. The basic idea of all approaches is to compare the situation before and after matching and check if there are remaining any differences after conditioning on the propensity score (Caliendo and Kopeinig, 2008).

(Rosenbaum and Rubin, 1983; Dehejia and Wahba, S., 2002), emphasize that the vital issue is to make sure whether the balancing condition is satisfied or not because it reduces the influence of confounding variables. There are different approaches to applying the method of covariate balancing between treated and non-treated individuals.

Standard bias: - One suitable pointer to assess the distance in marginal distributions of the X variables is the standardized bias (sb) suggested by (Rosenbaum and Rubin ,1985). It is used to quantify the bias between treated and control groups. For each variable and propensity score, the standardized bias is computed before and after matching as:

$$SB(X) = 100.\frac{\bar{x}_1 - \bar{x}_0}{\sqrt{0.5(V_1(X) + V_0(X)}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(16)}$$

$\bar{x}_0$ and $\bar{x}_1$, the sample mean for the treatment and control groups, and (V_1 (X), V_0 (X) is the corresponding variance (Caliendo and Kopeinig, 2008). The bias reduction (BR) can be computed as:

$$BR = 100(1 - \frac{B(X)_{after}}{B(X)_{before}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(17)}$$

One possible problem with the SB approach is that one does not have a clear indication of the success of the matching procedure.

T-test: A two-sample t-test is used to check if there are significant differences in covariate means for both groups (Rosenbaum and Rubin, 1985). Before matching, differences are expected, but after matching the covariates should be balanced in both groups, and hence no significant differences should be found. The t-test might be preferred if the evaluator is concerned with the statistical significance of the results. The shortcoming here is that the bias reduction before and after matching is not visible.

Joint significance and Pseudo-R2

Sianes (2004), suggests re-estimating the propensity score on the matched sample, i.e. only on participants and matched non-participants, and comparing the pseudo-R^2s before and after matching. The pseudo-R^2 indicates how well regressor X explains the participation probability. After matching there should be no systematic differences in the distribution of covariates between both groups and therefore the pseudo-R^2 should be fairly low.

Furthermore, one can also perform a likelihood ratio test on the joint significance of all covariates in the probit or logit model. The test should not be rejected before and should be rejected after, matching.

Estimation of Standard error

Testing the statistical significance of treatment effects and computing their standard errors is not a straightforward thing to do. The problem is that the estimated variance of the treatment effect should also include the variance due to the estimation of the propensity score, the imputation of the common support, and possibly also the order in which treated individuals are matched. These estimation steps add variation beyond the normal sampling variation (Heckman *et al*., 1998).

Bootstrapping: Standard errors in psmatch2 are invalid since they do not take into account the estimation uncertainty involved in the probit/logit regressions (pscore). One way to deal with this problem is to use bootstrapping as suggested by (Leeuwis, 2004). This method is a popular way to estimate standard errors in case analytical estimates are biased or unavailable. Recently it has been widely applied in most economic literature in impact estimation procedures. Each bootstrap draw includes the re-estimation of the results, including the first steps of the estimation (propensity score, common support).

Bootstrap standard errors attempted to incorporate all sources of error that could influence the estimates. (Abadie et al., 2006), argue that using the bootstrap after nearest neighbor matching, until recently a common approach to estimating standard errors in impact evaluation studies, does not yield valid estimates.

3.7.9. Sensitivity analysis

Recently checking the sensitivity of the estimated results becomes an increasingly important topic in the applied evaluation literature (Caliendo and Kopeinig, 2008). The matching method is based on conditional independence or unconfounded assumption, which states that the evaluator, should observe all variables simultaneously influencing the participation decision and outcome variables. This assumption is non-testable because the data are uninformative about the distribution of the untreated outcome for treated units and vice versa (Becker and Caliendo, 2007).

(Rosenbaum, 2002), proposes using Rosenbaum bounding approach to check the sensitivity of the estimated ATT for deviation from the CIA. The basic question to be answered here is whether inference about treatment effects may be altered by unobserved factors. In other words, one wants to determine how strongly an unmeasured variable must influence the selection process to undermine the implications of matching analysis.

The bounding approach does not test the unconfounded assumption itself, because this would amount to testing that there are no (unobserved) variables that influence the selection into treatment. Rosenbaum bounds provide evidence on the degree to which any significant results hinge/center/ on this attestable assumption. If the results turn out to be sensitive the evaluator might have to think about the validity of his identifying assumption and consider other estimation strategies.

As noted above it is not possible to estimate the magnitude of selection bias using observational data, instead, the sensitivity analysis uses the bounding approach that involves calculating upper and lower bounds using the Wilcoxon signed rank test. This rank tests the null hypothesis of the no-treatment effect for different hypothesized values of unobserved selection bias.

The central assumption of the analysis is that treatment assignment is not uncompounded given the set of covariates X. In addition, it is assumed that the CIA holds given X and an unobserved binary variable U. In other words the probability of treated household F(·) needs to be complemented by a vector U containing all unobservable variables and their effects on the probability of participation captured by γ.

$P(X, U) = \Pr(D=1/X, U) = F(X\beta + U\gamma) = e^{X\beta + U\gamma}$ …………………………… (18)

Where; γ is the effect of U on the probability of participation in the program.

Assuming that F follows logistic distribution, the odds ratio of two matched individuals (let's say m and n), who are identical in observable characteristics, receiving the treatment written as:

$$\frac{P(PX,u_m)}{P(X,u_n)} X \frac{(1-P(X,u_n)}{(1-P(X,u_m)} = \frac{e^{\beta_m X_m + \gamma_m u_m}}{e^{\beta_n X_n + \gamma_n u_n}} = e^{[\gamma(u_n - u_m)]} \text{ .... } (19)$$

Equation (19) states that two units with the same **X** differ in their odds of receiving the treatment by a factor that involves the parameter $\boldsymbol{\gamma}$ and the difference in their unobserved covariates U. As long as there is no difference in U between the two individuals or if the unobserved covariates have no influence on the probability of participating in cattle artificial insemination adopting ($\boldsymbol{\gamma}$ = 0). This happens if the probability of participant was only determined by the **x** vector and the selection process is random. $\boldsymbol{\gamma} > 0$ implies that two individuals with the same observed characteristics have different chances of participating in the program due to unobserved selection bias. In our sensitivity analysis, we examined how strong the influence of $\boldsymbol{\gamma}$ on the participation in artificial insemination technology to attenuate the impact of adopting artificial cattle insemination on household well-being.

Both matched individuals have the same probability of participating only if e^{γ} = provided that they are identical in X. Consequently there will be no selection bias on unobservable covariates. If e^{γ} =2, one of the matched individuals may be twice as likely to participate in an artificial insemination adoption program as the other agent (Rosenbaum, 2002).

If e^{γ} is close to one and changes the inference about the treatment effect, the impact of artificial insemination adopting household on potential outcomes, the estimated effect is said to be sensitive to hidden bias. In contrast, insensitive treatment effects would be obtained if a large value e^{γ} does not alter the inference about treatment effects.

In this sense e^{γ} can be interpreted as a measure of the degree of departure from a study that is free of unobservable selection bias (Rosenbaum, 2002). Several values of e^{γ} bounds are calculated on the significance level, and hence, the null hypothesis of no effect of artificial insemination technology adoption on potential outcomes is then tested. Eventually, using predicted probabilities of participation in the program (i.e. propensity score) match pairs are constructed using alternative methods of matching estimators.

Then the impact estimation is the difference between the simple mean of the outcome variable of interest for participant and non-participant households. The difference in involvement in participation of AI service between treatment and matched control households is then computed. The ATT is obtained by averaging these differences in household well-being outcomes (Y_i) across the k-matched pairs of households as follows:

$$\mathrm{ATT} = \sum_{i=0}^{k} [Y_i^{i\epsilon D=1} - Y_i^{i\epsilon D=0}] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (20)$$

A positive (negative) value of ATT suggests that households who have participated in the program have increased (decreased) outcome variable Y_i non-participants.

3.8. Variable Choice and Its Definitions

3.8.1. Choice of variables

In the estimation of the propensity score, we are not interested in the effects of covariates on the propensity score because the purpose of our work is to evaluate the impact of using AI technology for a dairy cow on the well-being of smallholders' using the different aspects of well-being as an indicator.
However, the choice of covariates to be included in the first step (propensity score estimation) is an issue. (Heckman *et al.*, 1998), argue that omitting important variables can increase the bias in the resulting estimation.

In our particular case, variables that determine households' decision to adopt AI for cattle breeding could also affect the outcome variable mentioned above. Here, pre-intervention characteristics, which bring variation in outcomes of interest among users and non-users, were used. In other words, variables that are not affected by being a user of the AI service or not or those explanatory variables which are fixed throughout are used as explanatory variables.

There are no general rules for which variables to include in the model (Andersson *et al.*, 2009). But the present study was guided by economic theory and empirical studies to know which observables (explanatory variables) affect both adoption and the outcomes of interest (Bryson *et al.*, 2002).

Table 2: Types, definition and measurement of variables

Variable	Type	Definition	Measurement
Dependent Variable			
Treatment	Dummy	Adopter or non-adopter	1 if adopter, 0 otherwise
Outcome Variable			
LVSINC(Livestock income)	Continous	Income from sale of live animal and animal productsr	Ethiopian birr
MINC (milk Income)	Continuous	Milk income per year	Ethiopian birr
TOTALEXP (Total household expenditure)	Continuous	The amount of money households spend for food and non- food expenditures	Ethiopian birr
Covariant			
AGHH	Continuous	Age of the household head	In year
SEXHH	Dummy	Sex of the household head	1 if male,0 otherwise
EDHH	Dummy	Education level of household head	0 if not educated, 1 if primary, 2 if secondary, 3 if College and above
ACGLN	Dummy	Access to Grazing Land	1 if yes, 0 if no
FAMSIZ	Continuous	Number of family in given household	In number
MOPHO	Dummy	Having mobile phone	1 if yes, 0 if no
KWHTDCT	Dummy	Knowledge of heat detection	1 if yes, 0 if no
NFAINC	Continuous	Non-farm income	Ethiopian birr
FAINC	Continuous	Farm income	Ethiopian birr
TIMAI	Dummy	On time delivery of the service	1 if timely available, 0 otherwise
PERCAI	Dummy	Perception about the importance of AI	1 if important, 0 if not important

Source own computed, 2014 E.C

3.8.2. Definition of Variables and Working Hypotheses

3.8.2.1. Outcome variables

To measure the impact of adopting AI on the well-being of households three indicators were used to assess the impact of the technology on the household wellbeing; income from sales of animals, milk income, and total consumption.

Livestock income: This is a continuous variable and it is one of the outcome variables that represent households' income from sales of live animals and livestock products. This is measured by calculating the total annual livestock income of households from different sources like the sale of milk products such as butter, yogurt, sale of live animals, and sale of animal byproducts, and the like.

Income from milk: It is a continuous and second outcome variable in this case that state AI user households own genetically higher cattle type and they are expected to produce more volume of milk than nonuser households and they receive more amount of money. The impact of using and not using artificial insemination on the well-being of the sample households is measured by using annual milk income during the 2013 production year in this study.

Household annual consumption: It is a continuous outcome variable which is measured in Ethiopian birr in this study. It is the total household spending on different goods and services such as food and non-food measured on annual basis.

3.8.2.2. Independent variables

Age of the household head: It is a continuous variable and is measured in a number of years. In this study, the age of the household head is expected to affect AI technology adoption. As the age of the household increase, the probability of adoption decreases. Because with the age, a farmer becomes inactive in participation or becomes risk-averse to new technologies. And younger farmers are expected to take the risk due to their longer planning horizons (Rajeswari *et al.*, 2020). Therefore, users household heads are expected to be relatively younger.

Sex of the household head: It is a dummy variable, and takes a value of 1 for males and 0 for females. Due to socio-economic activity and engagement, the role of male and female involvement in the technology adoption process through different extension programs, and access to information, it is hypothesized that male-headed households are in a better position for information.

Education level of household head: is a categorical variable which is measured qualitatively. It refers to the educational status of the household head whether educated or not. Education is very vital to adopting new technology and also education improves the readiness of farmers to accept new technologies. Education increases farmers' ability to obtain process and use information (Paulos *et al*., 2004). In the present study, it was expected to a positive relationship between education and the use of artificial insemination services.

Access to grazing land: It is a dummy variable taking values 1 for yes and 0 for no. Adopters of artificial insemination were expected to have more cows, so availability of feed is a crucial factor and it is hypothesized that households with accessible enough grazing land are expected to be users of artificial insemination technology.

Family size: It is a continuous variable that shows the number of family members in the household. As active labor accessibility increases, it also will have a positive influence on the adoption of improved AI technology. Members of the household have different responsibilities for different dairy herd operations and herd management practices (Berhanu, 2012). Based on these points it is hypothesized that households with higher family members have better opportunities to use AI and households with fewer family members are assumed to be non-users.

Holding mobile phone: Having a mobile phone is an essential categorical variable determining factor and helps to get AI beneficiaries quick service from the AI to take their cows when coming to heat. It takes a value of 1 for yes and 0 otherwise. It is hypothesized that having a mobile phone positively influences a household's decision to use AI service because a household head having a mobile phone is not expected to go to AI technicians as he can just call and communicate with them and they are not delayed by the long distance from their home to technicians' office.

Knowledge of heat detection: Heat is a dummy variable that represents a period of acceptance for mating (sexual receptivity) that normally occurs in non-pregnant cows. This period of receptivity may last from 6 to 30 hours and occurs every 21 days on average. To achieve the goal of AI, farmers must be well educated in heat detection and check for heat regularly in the herd (Galloway and Perera, 2006). So it is hypothesized that when farmers can detect heat they are motivated to adopt the AI than the others

Non-farm income: It is an income that is generated out of the farm without using products that are produced on one's farm. Availability of non-farm income is found to be one of the factors that influence the use of AI positively (Berhanu, 2012). Due to this, several household members that involve in off-farm activities are expected to have more chances to get more income.

Farm income: An income obtained directly from crop and livestock activities. In the present study, the decision to use AI technology for cattle cross-breeding is hypothesized to have a positive relationship with farm income. When farmers have more disposable income they become willing to use AI technology. Previous studies also indicate that farm income positively influences the use of new agricultural technologies (Fader *et al*., 1985).

Timeliness of AI service: It is a categorical variable that represents the timely availability of the service. Farmers should get the service at the time when they report that their cow is on heat. Research done on ten purposively preferred areas of five regional states of Ethiopia has discovered that 93% of the farmers who participated in the questionnaire survey respectfully demonstrated that they were not getting reliable and consistent AI service and 81% of them explained the reason for failure to be the absence of service on weekends & holidays, (Habtamu *et al.*, 2013).

Perception about the AI service: It is a dummy variable that measures the perception of sample households about the importance of AI services. People are living socially in certain physical and social environments (Olana *et al.*, 2003). Perception is a process by which we receive information or stimuli from our environment and transform it into psychological awareness.

Distance from AI Center: It is a continuous variable and measured in kilometers. Distance from the AI center was expected to affect the AI adoption. The AI center is usually strategically located within the farming areas and it is the place where the local extension worker and AI technician are stationed. As the distance from these centers (DAIC) increases, livestock technology like AI adoption decreases because this causes transport costs incurred in obtaining information on technologies and inputs to increase.

Total Livestock holding: It is a continuous variable that shows the number of livestock household owned/or captured as the number of livestock owned by the household. The relationship between livestock size and adoption and the intensity of AI adoption was expected to be positive. Households with larger livestock are more likely to adopt AI technology (Kaaya et al., 2005).

Before proceeding to estimate the data using the logit model, different tests should be undertaken. The presence of multi-colinearity among the variables seriously affects the parameter estimates of any regression model.

The Variance Inflation Factor (VIF) technique was employed to detect the problem of multi-co linearity for the continuous variables (Gujarati,2004). VIF can be defined as;

$$V_i f_{Xi} = \frac{1}{\mathbf{1} - {R_i}^2}$$

The larger the value of VIF, the more troublesome it is. As a rule of thumb, if a VIF of a variable exceeds 10, the variable is said to be highly collinear. Similarly, for dummy variables contingency coefficients test was employed as;

$$C = \sqrt{\frac{x^2}{n + x^2}}$$

Where C is contingency coefficient, x^2 is the chi-square value and n= total sample size. For dummy variables, if the value of contingency coefficient is greater than 0.75, it is an indication of the existence of the multicollinearity problem among them.

Heteroscedasticity exists when the variances of all observations are not the same, leading to consistent but inefficient parameter estimates. In this study, heteroscedasticity was detected by the Breusch-Pagen test (hettest) using STATA software version 13, and the propensity scores matching algorithm (psmatch2) developed by Leuven and Sianes, (2003) was used to assess the impact of artificial insemination.

CHAPTER FOUR

RESULT AND DISCUSSION

This section consists of two sub-sections. The first one is a description of sample households' characteristics. Under descriptive statistics, important characteristics of households and outcome variables are analyzed with appropriate statistical tools like mean, standard deviation, and percentages. The second sub-section is estimation results which include propensity score matching, treatment effect and sensitivity analysis results presented in detail.

4.1. Description of Sample Household Characteristics

4.1.1. Demographic and Socioeconomic characteristics of sample household

This sub-section has described the household characteristics that explain the information on demographic, and socio-economic characteristics which is assumed that either positive or negative influence on adoption decision of AI technology.

The summary of socioeconomic features of the household along with the mean difference test (t-test) of continuous variables is presented in (Table-3) below. After estimating the mean values, the significance of the mean difference test was undertaken by a two-group mean comparison test for the continuous variables. The distribution of the categorical variables related to the adopter and the non-adopter household was presented in Table 4 below. The proportion of the respondents falling into these categories is given and the differences in the proportion across adopter and non-adopter households were tested by using the chi-square test.

Age of the household head (logAge): The mean age of the total sample households in the study area was 3.7156 years with minimum and maximum ages of 2.94 and 4.45 years. Whereas the mean age of non-adopters was 3.76141 years with minimum and maximum ages of 3.04 and 4.45 years, respectively, and that of the adopter was 3.61997 years, with minimum and maximum values of 2.94 and 4.06 years, respectively (the value of the variable is in logarithm form). The descriptive analysis revealed a significant difference in the age of household heads between users and non-users of the technology at a 1% level of significance (Table-3). The result indicated that the age of non-adopter household heads was higher as compared to adopter household heads in the study area as was expected.

Family size (logFAMSIZ): The mean family size of the total sample households in the study area was about 1.720134, with minimum and maximum family sizes of 0.6931472 and 2.639057. Whereas the mean family size of non-adopter households was 1.648373 with a minimum and maximum of 0.6931472 and 2.639057, although the mean of adopter households was 1.86979 with a minimum and maximum family size of 0.6931472 and 2.397895, (values are in logarithm form).

The descriptive analysis implies that there was a significant difference in the family size of households between adopter and non-adopter households in the study area at a 1% level of significance.

Non-farm income (SQR_NFAINC): The mean annual non-farm income of the sample households in the study area was birr 90.29427, with minimum and maximum annual non-farm income of birr 0 and 189.842, respectively. But the mean annual non-farm income of a non-adopter household was birr 84.94783 with minimum and maximum annual non-farm income of birr 0 and 177.1384 respectively, whereas that of the adopter household is birr 101.4441, with minimum and maximum annual non-farm income of birr 0 and 189.842 respectively.

The descriptive analysis revealed that there was a significant difference in the annual non-farm income of households between adopters and non-adopter in the study area at a 1% significance level.

Livestock holding of sample households (SQR_TLU): The mean value of livestock of total sample household which is measured in the Tropical Livestock Unit (TLU) is 3.460221 with a minimum and a maximum number of 1.414214 and 5.196152, Livestock respectively, and that of adopter respondents was 3.761268, with minimum and maximum values of 2 and 5.196152, respectively and that of non-adopter households is 3.315867, with minimum and maximum mean values of 1.414214 and 5, respectively all the values here are in square root form. Households that have a large amount of livestock has participated in the technology more than those who have a smaller amount of livestock which is consistent with the hypothesized sign.

Distance from AI Center (SQR_DAIC): The mean distance from the artificial insemination center to the sample household which is measured in k/m is 1.415 with a minimum and a maximum distance of 0.442136 and 3.162278 k/m, respectively, and the mean distance from adopter households to the artificial insemination center was 1.383667, with minimum and maximum mean values of 0.4472136 and 2.828427, respectively and that of non-adopter households to the AI center is 1.65134, with minimum and maximum mean values of 0.4472136 and 3.162278, respectively (all the values were transformed to square root form). The descriptive analysis indicates that there is a significant difference in distance between the user and non-user households to the artificial insemination center.

Education level: The proportional years of the education level of the sample households in the study area were primary education of schooling, whereas the adopter households had a maximum and minimum education level of primary and illiterate. And the proportional education level of non-adopter households had a maximum and minimum education level of primary and College/ & above schooling. The chi-square value which is 36.74 indicates that there is a significant difference in education level between user and non-user household heads.

Timely availability of AI Service (TIMAI): Out of the total sample respondents about 78.95% of them reported the service is available on time while 21.05% of them have reported timely unavailability of the service, whereas the proportion of timely availability of service reported by a user and non-user respondents were about 88.89% and 82.38%, respectively, and the proportion of timely unavailability of service reported by user and non-user households were about 11.11% and 17.62%, respectively. The chi-square test on this variable indicates that there was a significant difference b/n adopter and non-adopter households at a 1% level of significance.

Knowledge of heat detection: In this specific study from the total sampled households, about 85.60% know how to detect heat period while 14.40% of them do not know about detecting the heat period, as the same time 92.31% of users households know how to detect heat period but only 7.69% of them have no skill to detect the heat period, and the proportion of non-user households who have the skill and have no skill to detect heat period were about 82.79% and 17.21%, respectively. The chi-square test of this variable shows that there is a statistically significant difference between the two groups at a 1% probability level.

Perception about the AI service: Mostly the entire user households perceive that it is an important technology and 84.8% of the non-adopter households also responded that AI is important, and 15.16% of them felt that it is not important. There is a statistically significant difference in perception of the importance of AI between the user and non-user households at a 1% probability level.

Holding mobile phone: Out of the total sample respondents, about 53.46% of them have a mobile phone while 46.54 % of them have no mobile phone, whereas the proportion of adopter and non-adopter respondents holding a mobile phone were about 66.67% and 47.13%, respectively, and the proportion of not holding mobile phone adopter and non-adopter households were about 33.33% and 52.87%, respectively. The chi-square test result on this variable indicates that there was a significant difference between adopter and non-adopter households at a 1% level of significance.

Access to grazing land: Regarding the accessibility of grazing land out of the total sampled households, about 69.25% of the total household heads have access to grazing land, whereas the proportion of adopter and non-adopter households with access to grazing land was about 83.76% and 62.30%, respectively which accounts 69.25% of the total household heads. Whereas the proportion of adopter and non-adopter household heads that lack access to grazing land was 16.24 % and 37.70% respectively, this is 30.75 % of the total sampled household heads. The chi-square test result on this variable shows that there was a significant difference between adopter and non-adopter households at a 1% significant level.

Table 3: Descriptive statistics of sample households (for continuous variables)

Pre-intervention	Sample household (N=361)		Adopter households (n=117)		Non-adopter households(244)		Difference in mean & STD		T_value
Variable	Mean	STD	Mean	STD	Mean	STD	Mean	STD	
logAge	3.7156	0.0138	3.6199	0.0235	3.7614	0.0163	0.1414	0.0287	4.936***
logFAMSIZ	1.7201	0.0201	1.8698	0.0283	1.6484	0.0253	-0.2214	0.0415	-5.341***
SQR_NFAIN	90.294	2.2401	101.44	4.281	84.948	2.5378	-16.496	4.713	-3.500***
SQR_DAI	1.6415	0.0332	1.3837	0.0503	1.7651	0.0405	0.3815	0.068	5.6063***
logFAINC	10.096	0.0225	10.107	0.0433	10.091	0.0261	-0.0162	0.0481	-0.3369
SQR_TLU	3.4602	0.0348	3.7613	0.0548	3.3159	0.0413	-0.4454	0.0707	-6.297***

Source: own survey result, (2022), *** means significant at the 1%, probability levels.

Table 4: Descriptive statistics of sample households (for dummy variables)

Variables	Category	Adopter(n=117)	Non-adopter(n=244)	Total(N=361)	$\chi 2$
SEXHH	Male	99(84.62 %)	199(81.56%)	298(82.55%)	0.513
	female	18(15.38%)	45(18.44%)	63(17.45%)	
EDLE_HH	Illiterate	17 (14.53 %)	77 (31.56 %)	94(26.04 %)	36.74***
	primary e	64 (54.70%)	148 (60.66 %)	212(58.73%)	
	Secondary	31 (26.50 %)	16 (6.56 %)	47(13.02%)	
	College & above	5(4.27 %)	3(1.23%)	8(2.22%)	
TIMAI	not timely available	13(11.11%)	63 (17.62 %)	76(21.05%)	10.29***
	timely available	104(88.89%)	201(82.38%)	285(78.95%)	
KWHTDCT	not Know how to detect	9 (7.69 %)	43(17.21%)	52(14.40 %)	6.325***
	Know how to detect	108(92.31 %)	202(82.79%)	309(85.60 %)	
PERCAI	Not important	1(0.85%)	37(15.16%)	38(10.53%)	17.19***
	Important	116(99.15%)	207(84.8%)	323(89.47%)	
MOPHO	Have no mobile phone	39(33.33%)	129(52.87%)	168(46.54%)	12.13***
	Have mobile phone	78(66.67%)	115(47.13 %)	193(53.46%)	
ACGRLN	have no access	19(16.24%)	92(37.70%)	111(30.75%)	17.11***
	have access	98(83.76%)	152(62.30%)	250(69.25%)	

Source: Own survey (2014), *** means significant at the 1%, probability levels.

4.1.2. Descriptive statistics of outcome variables

The outcome variables of this study are, milk income, livestock income, and total household expenditure or total household consumption of the previous year (2013). The difference between the two groups (adopter and non-adopter) regarding the outcome variables are presented as follows.

Milk income (SQR_MLINC): This is a continuous variable and it is one of the outcome variables that represent sampled households' income from milk. The mean value of annual milk income of the sample households in the study area was birr 50.9256, with a minimum and maximum of birr 0 and 209.7618, respectively. But the mean annual milk income of non- adopter household was birr 32.10991 with a minimum and maximum of birr 0 and 109.5445 respectively, whereas that of the adopter household is birr 90.16516, with minimum and maximum annual milk income of birr 0 and 209.7618 respectively, all the values are presented in square root forms. There was a significant difference in the annual milk income b/n adopter and non-adopter households in the study area at a 1% significance level.

Livestock income (SQR_LVSINC): The mean annual livestock income of the sample households in the study area was birr 130.6529, with minimum and maximum annual livestock income of birr 22.36068 and 236.453, respectively. But the mean annual livestock income of a non-adopter household was birr 117.6178 with minimum and maximum annual livestock income of birr 22.36068 and 224.722 respectively, whereas that of the adopter household is birr 157.8371, with minimum and maximum annual livestock income of birr 81.24039 and 236.453 respectively, values are in square root form.

Household total annual consumption/expenditure: The mean value of the annual consumption of the sampled households in the study area was birr 42461.76 with minimum and maximum annual consumption of birr 10010 and 75482, respectively. But the mean annual consumption of non-user households was birr 37610.75, with minimum and maximum annual consumption of birr 10010 and 68225 respectively, whereas that of the user households was birr 52578.39, with minimum and maximum annual consumption of birr 32851 and 75482 respectively. The analysis revealed that there was a significant difference in the annual consumption of households between adopters and non-adopter households in the study area at a 1% significance level. This implies that the consumption of the user household was higher as compared to non-user households in the study area.

Table 5: Descriptive statistics of outcome variables

Pre-intervention	Sample HHs (N=361)		Adopter HHs (n=117)		Non-adopter HHs(244)		Difference in mean & STD		T_value
Variable	Mean	STD	Mean	STD	Mean	STD	Mean	STD	
SQR_MLINC	**50.926**	**2.3889**	**90.165**	**3.518**	**32.11**	**2.2759**	**-58.055**	**4.0909**	**-14.191*** **
SQR_LVSINC	**130.65**	**1.9196**	**157.84**	**2.856**	**117.62**	**2.013**	**-40.219**	**3.516**	**-11.439*** **
TOTALEXP	**42461.7**	**651.8**	**52578.4**	**854.66**	**37610.8**	**682.05**	**-14968**	**1149.2**	**-13.024*** **

Source: own survey result, (2022), *** means significant at the 1%, probability levels.

4.2. Empirical Result

The logistic regression model was used to estimate propensity score matching for the adopter and non-adopter households; whereas the Tobit model was used to identify the adoption intensity of AI technology in the study area.

Before proceeding with impact estimation Variance Inflation Factor (VIF) was conducted to test for the presence of a strong multicollinearity problem among the continuous explanatory variables. Moreover, by using contingency coefficients multicollinearity between discrete variables was checked all discrete explanatory variables are greater than the critical value. There was no explanatory variable dropped from the estimated model since no serious problem of multicollinearity was detected from the result of VIF showing less than the cut-off point which is 10.

Table 6: Multicollinearity test for continuous in variables

. vif

Variable	VIF	1/VIF
logFAMSIZ	1.18	0.849820
SQR_TLU	1.17	0.857181
logAge	1.16	0.863169
ACGRLN	1.15	0.867102
EDLE_HH	1.15	0.870404
MOPHO	1.12	0.889400
SQR_DAIC	1.12	0.893448
PERCAI	1.10	0.906997
SEXHH	1.06	0.941591
KWHTDCT	1.06	0.941746
TIMAI	1.06	0.945073
SQR_NFAINC	1.05	0.954327
logFAINC	1.02	0.985066
Mean VIF	1.11	

Source: Researchers' own computation, 2022

Similarly, heteroscedasticity was tested by using the Breusch-Pagan test. This test resulted in the rejection of the existence of the heteroscedasticity hypothesis and there was no need to make the standard error robust since there is no heteroscedasticity problem. In addition, a model specification was checked by using the Ramsey RESET test. The result from the stata-13 output p-value was 0.1733 which is greater than 0.05, therefore we accept H_0 meaning there is no model specification error indicating no variable is dropped from the model estimated. Finally, Goodness of Fit Test for Logistic Regression Model was conducted using Hosmer-Lemeshow Test. The result of the test indicates that our model fits reasonably well.

Hetroskedasticity test

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

chi2 (13) = 17.60

Prob > chi2 = 0.1733

Model specification Test

```
. estat ovtest

Ramsey RESET test using powers of the fitted values of treat
       Ho:  model has no omitted variables
                  F(3, 348) =      1.84
                   Prob > F =      0.1393
```

Goodness of fit test

```
. estat gof, group(10)

Logistic model for treat, goodness-of-fit test

  (Table collapsed on quantiles of estimated probabilities)

       number of observations =       361
             number of groups =        10
      Hosmer-Lemeshow chi2(8) =         8.60
                  Prob > chi2 =         0.3776
```

4.2.1. Determinants of AI chnology Adoption

The logit model was used to analyze the first objective of this study, which is to identify factors affecting participation in the adoption of artificial insemination technology in Yem special district. The maximum likelihood estimate of the logistic regression model result shows that the adoption of artificial insemination is significantly influenced by eight explanatory variables, while the rest of the five variables were not significant in explaining the variation in the dependent variable. These are, age and educational level of household head, distance to AI center, family size, livestock holding (TLU), timely availability of AI service, perception about the importance of AI, and access to grazing land are significant variables positively affecting the adoption of artificial insemination technology. The age of the household head and distance from the AI center to the farm are variables negatively and significantly affecting the adoption participation in the study area.

Age of household head (logAge): The marginal effect reveals that age of the household head found to be negative and significant relationship between adoption of artificial insemination technology at ($p<0.01$) level of significant with ($p=0.000$), which is consistent with the hypothesized sign. Accordingly, as the age of the household head increase by one year, decreases the probability of dairy technology adoption of the household by 44.51%.

With the age, a farmer becomes inactive to participating the technology issues or becoming risk-averse to new technologies. This suggests that the rate of AI adoption decreases as farmers get older. This finding is consistent with the study conducted by Khainga et al. (2015) and Quddus (2013) which found the age of the household head to be negatively associated with adoption decisions because younger farmers are less risk averse and are ready to invest in the long-term plan due to their age. However, it is contrary to a study by (Simon, 2006) that found a positive relationship between age and adoption of new technologies.

During the key informants' interview, woreda livestock expert Mr. Tadese Shifa and cluster level AI technician Mr. Danial Brihanu pointed out and testified that most adopter household heads are younger than non-adopter household heads in the study area. At the same time, the researcher during his survey for primary data collection has observed and confirmed that the adopter household heads are physically younger enough than those non-adopter household heads in the district.

Education level of household head(EDLE_HH): This result implies education level of household head found to be positive and significant effect on the adoption decision of artificial insemination technology at 1% significant level.. Regarding to the education level of household head increases by one year, the probability of artificial insemination technology adoption increases by 12.61%. The result shows that it has a positive relationship with AI adoption as was expected. These results show that most of the adopter household heads were fairly educated which could enable them to fairly adopt the technology. Similarly (Mishra, 2010) in his study has found that higher education level leads to ease of access to knowledge and information on agricultural technology undertakings. Consistent with the finding of this paper a study by (Knowler, 2007) and (Mishra, 2010), shows that the education level of the household head has a positive influence on artificial insemination technology adoption.

Distance from AI Center: The marginal effect in table 7 shows the distance from the AI center to the respondents' home was negatively signed and significant at a 1% level of probability. Thus, as the distance from AI center increase by one kilometrs, decreases the probability of AI technology adoption of the household by 13.65%. The possible reason behind this could be due to the costs incurred in the whole process of obtaining technical, information, and service from agricultural experts and AI technicians increased. This specific study has verified that dairy farmers who live closer to AI centers are more likely to adopt and use artificial insemination technology compared to their counterparts who live farther away from the respective centers. Similarly, (Quddus, 2012) in his study titled "*A*doption of dairy farming technologies by small farm holders" has postulated that distance from dairy technological centers can determine negatively the adoption participation among small dairy farmers. Also, this idea was supported by FGD and key informant discussants in the current study.

Tropical Livestock ownership (SQR_TLU): Livestock possession is an important indicator of household well-being status in rural Ethiopia. The marginal effect reveals that Livestock ownership of the household head found to be positive and significant relationship between adoption of artificial insemination technology at 1% level of significant. The justification for this positive relationship could be that if the household has numerous livestock, especially dairy cows make it is easy to participate in artificial insemination technology. The main reasons are household heads that have many TLU will have a better income and they can use their cow for insemination so it is easy for them to participate. Regarding to the Livestock ownership of household head if the number of cattle or cow increases by one, the probability of artificial insemination technology adoption increases by 16.29%. The finding is consistent with the hypothesized sign.

Key informant interviewees were also asked about the livestock possession status of households in the study area and their response shows that the adopter households have more livestock than non-adopters. During the FG discussion, adopter discussants said that having a large number of cattle has supported them to adopt artificial insemination. They said that if they have more number cows, there is an opportunity to obtain physically able-bodied cows from the herd to apply the technology. This finding has also been checked and evidenced by the researcher through his surveillance (observation) during data collection.

Timely availability of AI service: Similarly, timely availability of AI service resulted in an increases the likelihood of the household in the adoption of AI technology. When AI service is timely availability, the adoption of AI technolog differs by 10.36% with non-adopters. Timely availability of AI service is significant at a 1% level of significance and has positively influenced the adoption practice. The more the service is available on time, the more farmers become users. This finding is consistent with the studies conducted by (Yohannes, 2014) and (Tefera, 2015).

Access to grazing land: This result implies access to grazing land found to be positive and significant effect on the adoption decision of artificial insemination technology at 1% significant level. Concerning to the access to grazing land if grazing land increases by a one hectar, the probability of AI technology adoption increases by 16.57%. This implies that dairy farmers who access grazing land are more likely to adopt artificial insemination compared to those who have no access to grazing land.

Furthermore, the effects of this variable on the adoption of artificial insemination have been testified by the participants of FGD during the discussion. During the discussion, almost all artificial insemination user participants have confirmed that they have better access to grazing land than those non-adopter households. They have told that most of them have their own or individual grazing land and this makes the dairy farm activity easy for them.

Non-Farm income (SQR_NFAIN): Engaged in non-farm activities significantly and positively influence the probability of the household's in adoption decision of artificial insemination technology with p-value of (0.003). As the non-farm income increase by 1 birr, the probability of AI technology increase by 0.14%. As hypothesized, of source of additional income from off-farm activities increases the purchasing power of the household's different dairy technologies and farm input such as breed, feed and AI which helped to increase production and productivity. This result harmony with the work of (Ahmed *et al*, 2008).

This study has pointed out that, household heads that are involved in non-farm activities are more participating in the technology than household heads that are not involved in non-farm activities. The possible reason behind this could be due to household heads participating in the non-farm activities have better access to feeding for their dairy cows and input for their dairy cows like health costs. This is consistent with the study postulated by (Diiro, 2013) and (Tefera et al., 2014) that, non-farm activities help to overcome income constraints faced by rural households. This idea was supported and verified by FGD discussants in the current study.

Family size: The higher effect was accounted to large family size of the household in the artificial insemination technology. The marginal effect result shows that household with large family size found to be positive and higher marginal effect on adoption difference between participants and non- participant households. Family size positively influences the probability of the households in the decision of insemination technology with the p-value of (0.001). This implies that family size increase by one person, the probability of adoption increases by 27.52%. The possible reason behind this could be members of the household have different responsibilities for different dairy herd operations and herd management practices (Berhanu, 2012) and and (Dehinenet et al., 2014). This finding was supported and warranted by FGD discussants and the researcher's observation during a household survey.

Perception about the AI service: This result implies the respondent's perception about the importance of artificial insemination service found to be positive and significant effect on the adoption decision of AI technology at 1% significant level. Regarding to the respondent's perception about the importance of artificial insemination increases, the probability of AI technology adoption increases by 23.55%, which corroborates the hypothesized sign.

The finding of this study corroborates with the study conducted by (Yohannes, 2014) titled “The Impact of artificial insemination of a dairy cow on the livelihood of smallholder households in Haramaya District, Ethiopia”.

Table 7: Logistic regression for AI technology adoption

Variables	Odds Ratio	Marginal effect dy/dx	Std. Err.	Z	P-value
logAge	0.05263	-0.4451	0.03588	-4.32	0.000***
SEXHH	0.69836	-0.0583	0.28507	-0.88	0.379
logFAMSIZ	6.17428	0.2752	3.2543	3.45	0.001***
EDLE_HH	2.30283	0.1261	0.5686	3.38	0.001***
TIMAI	2.21197	0.10366	0.90254	1.95	0.052
KWHTDCT	2.28133	0.10313	1.2289	1.53	0.126
PERCAI	30.46	0.23559	35.3534	2.94	0.003***
MOPHO	1.11273	0.01611	0.3432	0.35	0.729
ACGRLN	3.56741	0.16576	1.30758	3.47	0.001***
logFAINC	0.8303	-0.0281	0.3001	-0.51	0.607
SQR_NFAIN	1.00986	0.00148	0.00334	2.97	0.003***
SQR_DAIC	0.40577	-0.1365	0.10738	-3.41	0.001***
SQR_TLU	2.93911	0.16298	0.84912	3.73	0.000***
_cons	0.48606		2.19375	-0.16	0.873

(*) dy/dx is for discrete change of dummy variable from 0 to 1
**** Significant at 1%, y = Pr (_Itreat_1) (predict) = .1856377*
Source: Computed from own survey(2022)

4.2.2. Determinants of the extent of AI adoption

The study has applied the Tobit model to assess factors related to the extent of artificial insemination technology adoption. In this study, the adoption intensity of the technology was measured in terms of the number of improved dairy cattle adopted. The Tobit regression model result shows that the adoption extent of artificial insemination is significantly affected by six explanatory variables, while the rest of the seven variables were not significant in explaining the adoption extent.

The statistical significance of six variables and their effect on the adoption intensity of artificial insemination technology for the variable education level, family size, livestock holding (TLU), perception about the importance of AI, and access to grazing land was positive and significant at a 1% level of significance, while the distance to AI center is negatively affecting the adoption extent.

Table 8 : Determinants of adoption extent

Tobit regression					Number of obs =	361
					LR chi2(13) =	136.19
					Prob > chi2 =	0.0000
Loglikelihood= -331.09787					Pseudo R2 =	0.1706
intesit	**Coef.**	**Std. Err.**	**t**	**P>|t|**	**[95% Conf.**	**Interval]**
logAge	-0.7780151	0.5030703	-1.55	0.123	[-1.767456	.2114258]
SEXHH	-0.3334657	0.3641364	-0.92	0.360	[-1.049651	.3827193]
logFAMSIZ	1.616421	0.4048216	3.99	0.000***	[.8202159	2.412626]
EDLE_HH	0.6583178	0.1968533	3.34	0.001***	[.2711459	1.04549]
TIMAI	0.42245	0.323689	1.31	0.193	[-.2141829	1.059083]
KWHTDCT	0.5414498	0.4241822	1.28	0.203	[-.2928336	1.375733]
PERCAI	3.044688	0.8871767	3.43	0.001***	[1.299785	4.789591]
MOPHO	0.1873889	0.2742245	0.68	0.495	[-.351957	.7267348]
ACGRLN	0.9693704	0.3300286	2.94	0.004***	[.3202688	1.618472]
logFAINC	-0.1032706	0.2938892	-0.35	0.726	[-.6812932	.474752]
SQR_NFAINC	0.0033459	0.0030069	1.11	0.267	[-.0025681	.00926]
SQR_DAIC	-0.9342058	0.2354638	-3.97	0.000***	[-1.397317	-.4710946]
SQR_TLU	0.8269059	0.2247793	3.68	0.000***	[.384809	1.269003]
_cons	-5.259482	3.780504	-1.39	0.165	[-12.69499	2.176029]
/sigma	1.872351	0.1402121			[1.596581	2.148121]

Source: Researcher 's own computation,(2022) *** Significant at 1%.

Education level of household heads: The results seen in the table-8 above show that more educated household heads or respondents have adopted more AI than those respondents with a less educational background which is significant at a 1% significance level. The finding shows that this variable affects the adoption extent positively in the study area.

Distance to the AI center: The distance from the AI center to the respondents' farm affects the extent of adoption of artificial insemination negatively and significantly at a 1% level. Specifically, an increase in distance to the AI center by 1 kilometer decreases the chance of intensifying the adoption of artificial insemination by 0.9342058%. The possible reason behind this could be due to accessibility of service which in turn reduces the transaction cost in term of searching for the insemination service. The result of the Tobit regression in table-8 shows that when the respondents' farm gets farther away from the artificial insemination centers the extent of the AI adoption decreased significantly at a level of 1%. The finding is consistent with the study conducted by (Tefera et. al., 2014) who found a negative relationship between distance from AI stations and the extent of artificial insemination technology adoption.

Family size: The family size of the household affects the extent of adoption positively and significantly at a 1% level of significance. The possible reason behind this could be the labor opportunity of those households. The Tobit model regression result shows clearly that households with larger family members have better opportunities to adopt AI technology compared to households with fewer family members. Households with large family sizes may not face labor shortages for their dairy farms. This means members of households have different responsibilities for different dairy herd operations and herd management practices, and this opportunity positively affects the extent of the adoption in the study area.

Similarly holding livestock has increased the adoption intensity of artificial insemination technology with a positive and significant coefficient at a 1% level of significance in the study area. In this specific study, it was verified that with a unit increase in livestock size the extent of adoption has increased by 0.0738037 on average.

Perception about the AI service: Optimistic perception about the importance of AI has positive and significant effects on the extent of AI adoption practices. This means having a constructive perception of artificial insemination encourages the willingness of farmers to intensify the use of AI services in the study area. The Tobit regression result indicated in table 8 above shows that there is a positive relationship between this variable and the adoption intensity of artificial insemination at a 1% level of significance. The econometric model result showed that the possibility of intensifying the adoption practice has increased by 2.71 as there is a unit increase in the perception of the importance of artificial insemination on average.

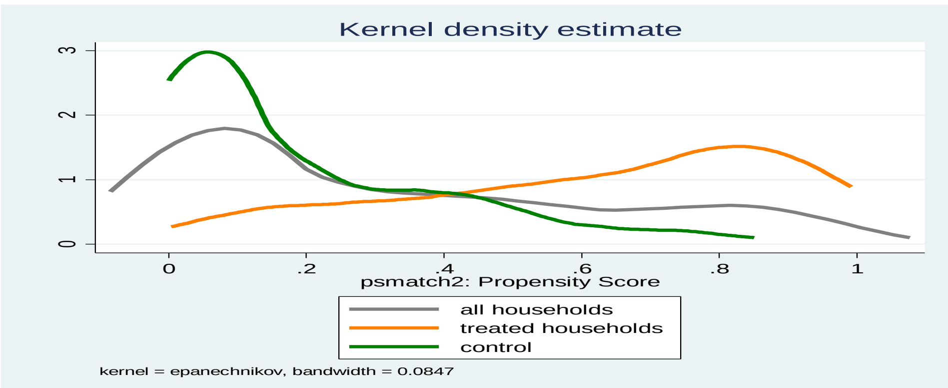
Access to grazing land: Households with access to grazing land are more likely to become users than those who lack grazing land. This variable has influenced the extent of AI adoption positively at a 1% level of significance in this specific study. The result of the Tobit model in table 8 above could be due to that since households have sufficient grazing land they are motivated to adopt AI technology. The Tobit regression result in table 8 showed that the possibility of intensifying the adoption practice has increased by 0.9693704 as there is a unit increase in the access to grazing land the other variables held constant in the model.

4.2.3. Estimation of propensity scores

Logistic regression was applied to estimate the propensity scores of sample households. The fairly low pseudo- R^2 of 0.38. A low R^2 value shows that program households do not have many distinct characteristics overall and as such finding a good match between program and non-program households becomes easier.

The distribution of the propensity score for each household included in the treated and control groups was computed based on the above participation model to identify the existence of common support. Figure 3 below depicts the distribution of the household concerning the estimated propensity scores. The figure shows that most of the treatment households were found in the middle and partly on the right side while most of the control households are partly found in the center and partly on the left side of the distribution. It also reveals that there is a wide area in which the propensity score of both treatment and control groups are similar.

Figure 3: Kernel density of propensity score distribution



Source: Computed from own survey(2014)

4.2.4. Matching adopter and Non-adopter Group

As stated before in above, four important tasks must be carried out before conducting the matching work itself. First, estimating the predicted values of program participation (propensity score) for all the sample households of both program and control groups (which was done in the previous section) is a primary activity. Second, imposing a common support condition on the propensity score distributions of households with and without the program is another important task. Third, discard observations whose predicted propensity scores fall outside the range of the common support region. And finally, sensitivity analysis should be done to check the robustness of the estimation (whether the hidden bias affects the estimated ATT or not).

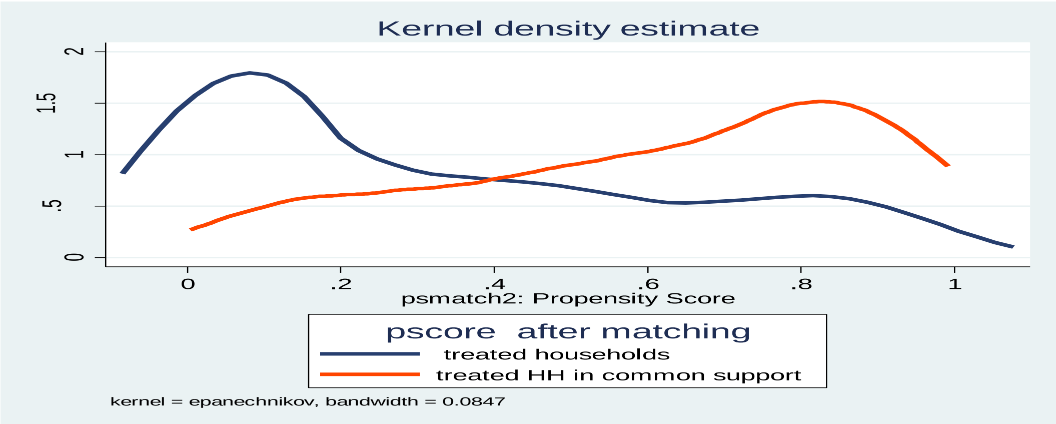
As shown in the Table 9, the estimated propensity scores vary between 0.0033287 and 0.9915505 (mean = 0.6155176) for adopter households and between 0.0000106 and 0.8501441 (mean = 0.1843625) for non-adopter (control) households. The common support region would, therefore, lie between 0.0033287 and 0.8501441 and the balancing property is satisfied to the final number of block 5. The number of blocks ensures that the mean propensity score is not different for treated and controls in each blocks. This means households whose estimated propensity scores are less than 0.0033287 and larger than 0.8501441 were not considered for the matching purpose. As a result of this restriction, 50 households were discarded. And it is good because the study does not drop abundant respondents from the sample in computing the impact estimator.

Table 9: Distribution of estimated propensity score

Groups	Obs	Mean	Std. Dev.	Min	Max
Totalousehlods	361	0.3240997	0.3055875	0.0000106	0.9915505
Adopter	117	0.6155176	0.2753976	0.0033287	0.9915505
Non adopter	244	0.1843625	0.2040701	0.0000106	0.8501441

Source: Own estimation result (2014)

Figure 4: Kernel propensity score of adopter household



Source: Own computed (2014)

4.2.5. Choice of matching algorithm

Different alternatives of matching estimators were tried in matching the treatment and control households in the common support region. The final choice of a matching estimator was guided by different criteria such as the equal means test referred to as the balancing test (Dehejia and Wahba, 2012), pseudo-R^2, and matched sample size. First, is the equal means test (referred to as the balancing test) which suggests that a matching estimator balance all explanatory variables (i.e., results in insignificant mean differences between the two groups) after matching. Second, looking into the pseudo- R^2 value, the smallest value is preferable. Third, a matching estimator that results in the largest number of matched sample sizes is preferred. To sum up, a matching estimator that balances all explanatory variables, with the lowest pseudo- R^2 value and, produces a large matched sample size is preferable. Table 10 presents the estimated results of tests of matching quality based on the three performance criteria. Looking into the result of the matching quality, it has been found that kernel matching with a bandwidth of (0.1) was found to be the best for the data we have at hand. Appendix 9 also shows that kernel matching with a bandwidth of (0.1) was found to be the best for AI adoption practice indicator variables. Hence, the estimation results and discussion for this study are the direct outcomes of the kernel matching algorithm with a band of 0.1. Finding a consistent estimate of the adoption impact on household wellbeing necessitates controlling for all such confounding factors adequately. In doing so, propensity score matching has resulted in 87 adopter households being matched with 224 non-adopter households (one to many matched) after discarding 30 participant and 20 control households households whose values were out of the common support region.

Table 10: Matching performance of different estimators

	Performance Criteria					
Matching algorithms	Balancing test*	Pseudo R^2	Matched sample size	MeanBias	Med bias	B
NNM						
NN(1)	12	0.052	311	11.8	9.0	53.9
NN(2)	13	0.020	311	7.5	7.0	33.6
NN(3)	13	0.011	311	5.4	4.0	24.6
NN(4)	13	0.010	311	4.7	5.5	23.5
NN(5)	13	0.006	311	3.6	3.6	18.7
Radius Caliper						
R. Caliper (0.01)	13	0.024	301	8.2	5.8	36.7
R.Caliper (0.25)	13	0.027	311	7.9	8.7	37.8
R.Caliper (0.5)	11	0.124	311	20.0	22.5	82.4
Kernel						
Band Width (0.1)	13	0.006	311	2.9	2.1	17.8
Band Width (0.25)	13	0.016	311	5.5	6.2	29.6
Band Width (0.5)	13	0.071	311	14.5	14.9	62.0

Source: own estimation result. *Number of explanatory variables with no statistically significant mean differences between the matched groups of adopter and non-adopter households.

4.2.6. Testing the Balance of Propensity Score and Covariate

After choosing the best performing matching algorithm the next task is to check the balancing of propensity score and covariate using different procedures by applying the selected matching algorithm (in our case kernel matching with a bandwidth of 0.1). As indicated earlier, the main purpose of propensity score estimation is not to obtain a precise prediction of selection into treatment, but rather to balance the distributions of relevant variables in both groups.

The balancing powers of the estimations were ensured by different testing methods. Reduction in the mean standardized bias between the matched and unmatched households, equality of means using t-test and chi-square test for joint significance of the variables used were employed here. The fifth and sixth columns of Table 11 show the standardized bias before and after matching, and the total bias reduction obtained by the matching procedure, respectively. The standardized difference in covariates before matching is in the range of 3.7% and 71.9 % in absolute value whereas the remaining standardized difference of covariates for almost all covariates lies between 0.2% and 12.4% after matching. This is fairly below the critical level of 20 %

suggested by Rosenbaum and Rubin (1985). Therefore, the process of matching creates a high degree of covariate balance between the treatment and control samples that are ready to use in the estimation procedure.

Similarly, t-values in Table 11 show that before matching all of the chosen variables except farm income and sex of household head exhibited statistically significant differences while after matching all of the covariates became insignificant and the variance ratio for all covariates after matching are less than the critical value which is two indicating covariates are fully balanced.

Table 11: Propensity score and covariate balance

Variable	Unmatched	Mean			%reduct	t-test	
	Matched	Treated	Control	%bias	|bias|	t	p>|t|
logAge	U	3.62	3.7614	-55.5	98.8	-4.94	0.000
	M	3.6788	3.6805	-0.7		-0.05	0.958
SEXHH	U	0.84615	0.81557	8.1	95.7	0.71	0.475
	M	0.85057	0.8519	-4.1		-0.02	0.980
logFAMSIZ	U	1.8698	1.6484	62.7	95.0	5.34	0.000
	M	1.826	1.8371	-3.2		-0.21	0.835
EDLE_HH	U	1.2051	0.77459	63.3	98.7	5.81	0.000
	M	1.092	1.0862	0.8		0.05	0.957
TIMAI	U	0.88889	0.7418	38.5	97.3	3.25	0.001
	M	0.86207	0.858114	1.0		0.07	0.941
MOPHO	U	0.66667	0.47131	40.1	84.9	3.53	0.000
	M	0.67816	0.70768	-6.1		-0.42	0.675
ACGRLN	U	0.83761	0.62295	49.7	94.8	4.23	0.000
	M	0.8046	0.7934	2.6		0.18	0.855
logFAINC	U	10.107	10.091	3.7	-236.0	0.34	0.736
	M	10.104	10.159	-12.4		-0.80	0.426
SQR_NFAINC	U	101.44	84.948	38.3	99.4	3.50	0.001
	M	93.492	93.393	0.2		0.02	0.987
PERCAI	U	0.99145	0.84836	54.5	93.5	4.24	0.000
	M	0.98851	0.97917	3.6		0.49	0.628
SQR_DAIC	U	1.3837	1.7651	-64.7	93.5	-5.61	0.000
	M	1.4634	1.4882	-4.2		-0.30	0.763
KWHTDCT	U	0.92308	0.82377	30.1	92.9	3.25	0.012
	M	0.91954	0.91252	2.1		0.17	0.868
SQR_TLU	U	3.7613	3.3159	71.9	99.2	6.30	0.000
	M	3.6685	3.6721	-0.6		-0.04	0.967

Source: Own estimation result,2022

The low pseudo-R^2 (0.006), the insignificant likelihood ratio tests, the Beta value which is minimized to 17.8 and less than 25, the R-value lies between the critical point, and the mean biase less than 20 support the hypothesis that both groups have the same distribution in covariates X after matching Table 12.

Table 12: Chi-square test for the joint significance of variables

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R
Unmatched	0.374	170.23	0.000	44.7	49.7	160.6*	0.57
Matched	0.006	1.39	1.000	2.9	2.1	17.8	1.66

Source: Own estimation result, (2022)

All of the above tests suggest that the matching algorithm we have chosen is relatively the best for the data at hand. This indicates that using this result we can examine the impact of adopting artificial cattle insemination technology on smallholder farmers milk income, livestock income, and on their total consumption among groups of households having similar observed characteristics. Thus, we can proceed to estimate the average treatment effect on the treated (ATT) for the sample households.

4.2.7. Estimating Treatment Effect on Treated (ATT)

To attain the stated objectives the following impact indicators of the treatment effect have been performed using the PSM model. In this section, the impacts of artificial insemination on outcome variables were evaluated for their significant impact on participant households, after pre-intervention differences were controlled.

Impact Estimate on Household annual Milk Income

The income of a household indicates the ability of a household to purchase its basic needs of life and hence it ultimately shows the well-being of the farm household as stated in Nguezet et al., (2011). Milk income is one of the most widely used proxy measures of household well-being in recent literature. The finding of current study shows that the milk income of adopter households is greater than that of non-adopter households (i.e. 93.9962459 vs 31.2544316). The AI adoption practice has positive and statistically significant at 1%, which is consistent with the hypothesized sign.

After controlling for differences in characteristics of the adopter and non-adopter households, it was found that, on average, the adopter household has increased annual milk income by 62.7418143 (66.75%) due to the adoption of artificial insemination.Artificial insemination service users (treated) groups yield a higher volume of milk than non-users (control) groups so they earn more milk income in agreement with the hypothesized sign. The finding is also consistent with the study by (Samuel et al., 2016) and (Yohannes, 2014).

Impact Estimation on Annual Livestock Income

Table 13 below shows that there are differences in livestock income among adopter and non-adopter households. The impact of using artificial insemination on livestock income shows a significant difference between the treated and control groups in the study area. Adopter households earn higher income from livestock and it shows a positively significant impact as was expected. This indicates the adoption of artificial insemination has a positive influence on the livestock income of the adopter households. The study shows that the livestock income of adopter households is greater than that of non-adopter (i.e. 153.86506 vs 122.649697) and the artificial insemination technology adoption practice has a positive impact on adopter households and is statistically significant at 1%. The finding is consistent with the study conducted by Samuel et al., (2016), titled ‘‘Adoption and Impacts of Dairy Production Technologies in Southwest Ethiopia: The Cases of Jimma and Ilu-Ababora Zones’’.

Impact Estimation on Household Total Consumption

The result shows that the consumption of adopter households significantly increased. The estimation result presented in Table 13 below shows that the total consumption of adopter households is greater than that of non-adopter households i.e, (52790.2299 vs. 41464.5354) indicating that adoption of artificial insemination technology has a positive impact and is statistically significant at 1%, which is consistent with the hypothesized sign.

As adopter households have better income opportunities they spend also more. After controlling for differences in characteristics of the adopter and non-adopter households, it was found that, on average, the adopter household has more expenditures or increased expenditures by 11325.6945 birr than non-adopter households due to using artificial insemination technology. The finding is consistent with the study conducted by (Hana, 2019), titled “Dairy technology adoption and its impact on household food security.

Table 13: Result of average treatment effect on treated household

Vaiable	Sample	Treated	Control	Difference	S.E	T_stata
SQRMLINC	ATT	93.9962459	31.2544316	62.7418143	6.26223697	10.02***
SQR_LVSINC	ATT	153.86506	122.649697	31.2153627	5.30494263	5.88***
TOTALEXP	ATT	52790.2299	41464.5354	11325.6945	1723.07012	6.57***

Source: Own estimation result(2022), *** means significant at a 1%, probability level.

4.2.8. Sensitivity Analysis

To control for unobservable biases, Table 14 below shows the result of sensitivity of artificial insemination effects on outcome variables. There may be hidden biases against the result of matching estimators and hence testing the robustness of the result is recommended. As it is not possible to estimate the magnitude of the selection bias with non-experimental data, the problem can be addressed by using a sensitivity test. The basic issue in testing sensitivity is to check whether the treatment effect is due to an unobserved factor or not. (Rosenbaum, 2002) proposes using Rosenbaum bounding approach to check the sensitivity of the estimated ATT.

Table 14: Result of sensitivity analysis using Rosenbaum bounding approach

Variables	e^{γ}=1	e^{γ}=1.25	e^{γ}=1.5	e^{γ}=1.75	e^{γ}=2	e^{γ}=2.25	e^{γ}=2.5	e^{γ}=2.75	e^{γ}=3
SQRMLINC	**P<0.000**	**P<0.000**	**P<0.000**	**P<0.000**	**P<0.000**	**P<0.000**	**P<0.000**	**P<0.000**	**P<0.000**
SQR_LVSINC	**P<0.000**	**P<0.000**	**P<0.000**	**P<0.000**	**P<0.000**	**P<0.000**	**P<0.000**	**P<0.000**	**P<0.000**
TOTALEXP	**P<0.000**	**P<0.000**	**P<0.000**	**P<0.000**	**P<0.000**	**P<0.000**	**P<0.000**	**P<0.000**	**P<0.000**

Source: Own estimation result (2022)

e^{γ} (Gamma)=log odds of differential due to unobserved factors where Wilcoxon significance for continuous variable and level for each significant outcome variable is calculated. Table 14 above denotes the critical level of e^{γ} (first row), at which the causal inference of significant artificial insemination effect has to be questioned. As noted by (Hujer et al., 2004), sensitivity analysis for insignificant effects is not meaningful and is therefore not considered here. Given that the estimated artificial insemination adoption effect is positive for the significant outcomes, the lower bounds under the assumption that the true treatment effect has been underestimated were less interesting (Becker and Caliendo, 2007) and therefore not reported in this study.

Rosenbaum bounds were calculated for artificial insemination adoption effects that are positive and significantly different from zero. The first column of the table shows those outcome variables which bear the statistical difference between treated and control households in our impact estimate above. The rest of the values which correspond to each row of the significant outcome variables are p-critical values (or the upper bound of Wilcoxon significance level - Sig^+ for continuous outcome variable and mantel heavens (mhbound) upper bound significance level for categorical variable) at a different critical value of e^{γ}**.** In this specific study, all outcome variables are continuous, and no need to conduct mantel heavens (mhbound). The result shows that the implication for the effect of the artificial insemination technology interventions is not changing though the participants and nonparticipant households have been allowed to differ in their odds of being treated up to 200% ($e^{\gamma} = 3$) in terms of unobserved covariates. That means for all outcome variables estimated at various levels of the critical value of e^{γ}, the p-critical values are significant which further indicates that we have considered important covariates that affected both participation and outcome variables. We couldn't get the critical value of e^{γ}, where the estimated ATT is questioned even if we have set e^{γ} largely up to 3, which a larger value compared to the value is set in different works of literature which is usually 2 (100%). Thus, we can conclude that our impact estimates (ATT) are insensitive to unobserved selection bias and are a pure effect of AI adoption.

CHAPTER FIVE

5. CONCLUSION AND RECOMMENDATION

5.1. Conclusion

This study aimed to analyze the impact of adopting artificial cattle insemination on smallholder farmers well-being the case of Yem Special District Ethiopia. Furthermore, the study aimed to identify the factors affecting the adoption of AI technology and the factor influencing the intensity of the adoption in the study area. Primary data were collected from 361 households from both adopter and non-adopter households using a structured questionnaire. In addition; focus group discussions and key informant interviews were applied to generate qualitative data.

The main question of the study was what would have happened to an outcome of interest had the program not been in place. Answering this question requires observing the outcomes of the adopter and non-adopter of the same group. However, it is impossible to observe the same object in two states simultaneously. While the evaluator observes the facts for an object, it is impossible to observe the counter-factual for the same object at the same time.

In non-experimental design, since the treatment placement creates a selection effect, simple with the and-without comparison of means for the adopter and non-adopter households would make biased estimates. Hence, the study has applied a propensity score matching technique which has become the most widely applied non-experimental tool for impact evaluation. It is used to extract comparable pairs of treatment-comparison households in a non-random selection setup and in the absence of baseline data. Moreover, it can adjust for (but not solve the problem of) selection bias and in estimating the counterfactual effects. The findings of this study showed that adopting artificial insemination technology has reward effects on the lives of adopter households in the district. As a result, adopter households in the district have better household well-being as it was expected.

The binary logistic regression model was used to analyze and identify factors affecting the adoption of artificial insemination. The adoption decision of households for the technology was significantly influenced by the age and education level of the household head, perception of the importance of AI, access to grazing land, non-farm income, distance to the AI center, family size, and livestock holding.

The result of Tobit regression revealed that six out of thirteen variables were found to have a significant effect on the adoption extent of artificial insemination technology. The variables are education level, perception about the importance of AI, access to grazing land, and distance to AI center, family size, and holding livestock are found to affect the extent of dairy technology significantly at a 1% significant level. Except for distance to the AI center which affects negatively the rest five variables affect the adoption extent positively.

In other words, matched comparisons of outcomes of interest were performed on these households that shared similar pre-treatment characteristics except those who have the effect of adopting artificial insemination. The resulting matches passed on many processes of matching quality tests such as t-test, reduction in standard bias, variance ratio for continuous variable R, B, P-value, and likely-hood ratio test, average mean bias, and chi-square test.

The impact estimation result indicates that there are significant differences in the interests of household wellbeing outcome variables between treatment and comparison groups, which could be attributable to the adopter household in adoption practice.

The finding of this paper shows that adopter households in the study area are associated with increased milk and livestock income which results in improving their household wellbeing. More specifically, their milk income was increased by birr 62.7418143 compared to non-adopter households. Similarly, income from livestock and total consumption of adopter households has a positive impact at a 1% significance level and 31.2153627, 11325.6945 birr increase respectively compared to non-adopter households which implies adopter’s household wellbeing was significantly affected by artificial insemination technology in the district. So based on this result toward improving the well-being status of the households in the district, the responsible bodies like regional and woreda agriculture offices in particular the livestock sub-sector should work together in development and awareness creation issues that endorse the adoption of the technology. Moreover, government institutions and other stakeholders in the study area should give due attention to publicizing and intensifying the adoption practice.

In this paper, the result of the Rosenbaum bounding procedure that was conducted to check the hidden bias due to unobservable selection shows that all estimated ATTs for all significant outcome variables are insensitive; which indicates its robustness (the treatment effect is exactly estimated by the adoption of artificial insemination technology). The results also serve to encourage future research on this topic, to find answers to the question of how adopter households, in particular, are more affected by this artificial insemination practice. This study is therefore to fill the information, literature, and methodology gaps to be used by academia, the government, local practitioners, and the people.

Generally, from this research, it can be concluded that adopting artificial cattle insemination technology broughts considerable impact on the well-being of rural households by creating opportunities and possibilities that amplify their income. This leads to the conclusion that adopting artificial insemination for dairy cows was one of the basic instruments to augment the leaving standard or the household well-being of the farming community in most rural parts of Ethiopia. Technology result tends to be optimized by addressing the possible influencing factors.

5.2. Recommendation

Our empirical findings in this paper provide evidence that adopting artificial insemination technology has played a key role in improving household well-being in rural areas. An attempt to develop the dairy production system of Ethiopia, the genetic improvement of dairy cows needs to undertake radical changes. Dairy farming needs to move out from the traditional subsistence attitude and develop a more productive approach. Artificial insemination is the best and most important technique ever devised for genetic improvement and development of the dairy sector. This directly contributes to the improvement of farmers' household well-being.

Based on empirical findings reported in this study, the following recommendations have been suggested for critical consideration in light of the discussion drawn herein before and conclude above.

The use of AI technology has greatly benefited the farmers' lives and has played a significant role in improving their household well-being in the study area. So, the government and concerned bodies should pay special attention to strength the adoption and expansion of the technology and thoroughly address the factors challenging the adoption participation and intensification of the technology in the study area.

HH heads should be encourage to use the technology because it increases the income of user as the current study finding shows.

The government and responsible bodies in particular the regional and the woreda agriculture office should work together in development and awareness creation issues that endorse the adoption of the technology

As formal education enhances farmers' ability to recognize and respond to new technologies, the government should pay attention to creating access to education for rural families.

Responsible bodies should give an appropriate emphasis to strength the policies and interventions that support the accessibility and grazing land management systems that ensure sustainable use of grazing lands and alleviation of feed shortage problems to initiate the adoption practice.

A proper weight should be given to ensuring timely availability of semen and liquid nitrogen. The AI centers should be opened nearby. An adequate number of AI technicians should be assigned in the district to make the service available at the time.

To make the AI service effective and easily manageable appropriate emphasis should be given to guarantee the availability of active labor.

The relevant institutions mainly the regional and woreda agricultural office, should employ the finding of this study as a starting point to decide and strengthen the continuation of this technology in the study area.

Further Study

The study only considers a few points from the broad concern of the impact of AI technology on household well-being. The study suggests the following points which this study was incapable to capture but require further investigation in the future in the study area.

To give a concert and sound conclusion further study will be important in the qualitative result of this study. In addition, the study only considered the positive impact of adopting AI technology on household well-being. However, the negative impacts of artificial insemination technology were not addressed in this study. Therefore, further study will be needed on the negative impacts of AI on household well-being in the study area.

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Appendix

Appendix 1: Conversion factor of tropical livestock unit (TLU)

LivestockCategory	TLU	LivestockCategory	TLU
Ox	1	Horse	1.1
Cow	1	Sheep (adult)	0.13
Woyefen	0.34	Sheep (young)	0.06
Heifer	0.75	Goat (adult)	0.13
Calf	0.25	Goat (young)	0.06
Donkey(adult)	0.7	Hen	0.013
LivestockCategory	TLU	LivestockCategory	TLU

Source: Stock, et al., 1991

Appendix 2: The Descriptive Statistics of out come variables

```
bysort treat: sum SQR_MLINC SQR_LVSINC TOTALEXP
```

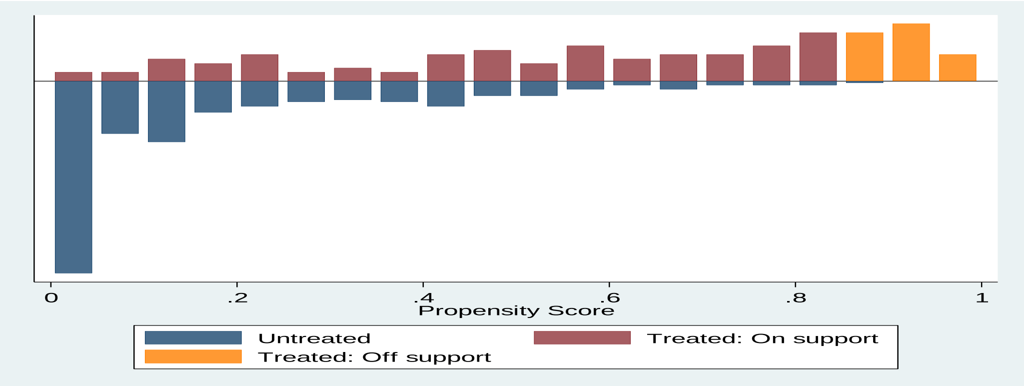
-> treat = untreated

Variable	Obs	Mean	Std. Dev.	Min	Max
SQR_MLINC	244	32.10991	35.55131	0	109.5445
SQR_LVSINC	244	117.6178	31.44344	22.36068	224.722
TOTALEXP	244	37610.75	10653.99	10010	68225

-> treat = treated

Variable	Obs	Mean	Std. Dev.	Min	Max
SQR_MLINC	117	90.16516	38.05616	0	209.7618
SQR_LVSINC	117	157.8371	30.89225	81.24039	236.453
TOTALEXP	117	52578.39	9244.603	32851	75482

Appendix 3: Histogram of propensity score



Appendix 4: Testing estimate of propensity score

Variable	Obs	Mean	Std. Dev.	Min	Max
pscore	361	.3240997	.3055875	.0000106	.9915505

sum pscore if treat

Variable	Obs	Mean	Std. Dev.	Min	Max
pscore	117	.6155176	.2753976	.0033287	.9915505

sum pscore if treat==1

Variable	Obs	Mean	Std. Dev.	Min	Max
pscore	117	.6155176	.2753976	.0033287	.9915505

sum pscore if treat==0

Variable	Obs	Mean	Std. Dev.	Min	Max
pscore	244	.1843625	.2040701	.0000106	.8501441

Appendix 5: Estimation of logistic regression model

```
. xi:logistic i.treat logAge i.SEXHH logFAMSIZ EDLE_HH i.TIMAI i.KWHTDCT i.PERCAI i.MOPHO i.ACGRLN logFAINC
> SQR_NFAINC SQR_DAIC SQR_TLU ,r
i.treat          _Itreat_0-1        (naturally coded; _Itreat_0 omitted)
i.SEXHH          _ISEXHH_0-1        (naturally coded; _ISEXHH_0 omitted)
i.TIMAI          _ITIMAI_0-1        (naturally coded; _ITIMAI_0 omitted)
i.KWHTDCT        _IKWHTDCT_0-1      (naturally coded; _IKWHTDCT_0 omitted)
i.PERCAI         _IPERCAI_0-1       (naturally coded; _IPERCAI_0 omitted)
i.MOPHO          _IMOPHO_0-1        (naturally coded; _IMOPHO_0 omitted)
i.ACGRLN         _IACGRLN_0-1       (naturally coded; _IACGRLN_0 omitted)

Logistic regression                               Number of obs   =        361
                                                  Wald chi2(13)   =      77.87
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -140.72112                 Pseudo R2       =     0.3812
```

_Itreat_1	Odds Ratio	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
logAge	.0526324	.0358807	-4.32	0.000	.0138347	.2002334
_ISEXHH_1	.698364	.2850659	-0.88	0.379	.3137827	1.554299
logFAMSIZ	6.174282	3.254298	3.45	0.001	2.197561	17.3473
EDLE_HH	2.302829	.5686047	3.38	0.001	1.419341	3.736257
_ITIMAI_1	2.21197	.9025409	1.95	0.052	.9941846	4.921432
_IKWHTDCT_1	2.281326	1.228902	1.53	0.126	.7937123	6.557096
_IPERCAI_1	30.45995	35.35344	2.94	0.003	3.131695	296.2641
_IMOPHO_1	1.112732	.3432016	0.35	0.729	.6079295	2.036704
_IACGRLN_1	3.567412	1.307581	3.47	0.001	1.739235	7.317256
logFAINC	.8303041	.3001025	-0.51	0.607	.4088666	1.686137
SQR_NFAINC	1.009858	.0033374	2.97	0.003	1.003338	1.01642
SQR_DAIC	.4057742	.1073803	-3.41	0.001	.241563	.6816141
SQR_TLU	2.93911	.8491161	3.73	0.000	1.668406	5.177619
_cons	.4860624	2.193746	-0.16	0.873	.00007	3376.15

```
. mfx

Marginal effects after logistic
      y  = Pr(_Itreat_1) (predict)
         =   .1856377
```

variable	dy/dx	Std. Err.	z	P>|z|	[95% C.I.	]	X
logAge	-.445127	.10133	-4.39	0.000	-.643736	-.246518	3.71557
_ISEXH~1*	-.0582965	.06935	-0.84	0.401	-.194222	.077629	.825485
logFAM~Z	.2752003	.07854	3.50	0.000	.121265	.429135	1.72013
EDLE_HH	.126102	.03781	3.34	0.001	.052001	.200203	.914127
_ITIMA~1*	.103663	.04822	2.15	0.032	.009145	.198181	.789474
_IKWHT~1*	.1031264	.05401	1.91	0.056	-.002723	.208975	.855956
_IPERC~1*	.2355905	.03586	6.57	0.000	.165304	.305877	.894737
_IMOPH~1*	.0161116	.04672	0.34	0.730	-.075452	.107676	.534626
_IACGR~1*	.1657583	.0422	3.93	0.000	.083047	.24847	.692521
logFAINC	-.0281132	.05385	-0.52	0.602	-.133649	.077423	10.0962
SQR_NF~C	.001483	.00049	3.02	0.003	.000521	.002445	90.2943
SQR_DAIC	-.1363548	.03705	-3.68	0.000	-.208967	-.063742	1.6415
SQR_TLU	.1629842	.04197	3.88	0.000	.080722	.245247	3.46022

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Appendix 6: Estimation of Tobit regression model

```
Tobit regression                                  Number of obs   =        361
                                                  LR chi2(13)     =     136.19
                                                  Prob > chi2     =     0.0000
Log likelihood = -331.09787                       Pseudo R2       =     0.1706
```

intesit	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
logAge	-.7780151	.5030703	-1.55	0.123	-1.767456	.2114258
SEXHH	-.3334657	.3641364	-0.92	0.360	-1.049651	.3827193
logFAMSIZ	1.616421	.4048216	3.99	0.000	.8202159	2.412626
EDLE_HH	.6583178	.1968533	3.34	0.001	.2711459	1.04549
TIMAI	.42245	.323689	1.31	0.193	-.2141829	1.059083
KWHTDCT	.5414498	.4241822	1.28	0.203	-.2928336	1.375733
PERCAI	3.044688	.8871767	3.43	0.001	1.299785	4.789591
MOPHO	.1873889	.2742245	0.68	0.495	-.351957	.7267348
ACGRLN	.9693704	.3300286	2.94	0.004	.3202688	1.618472
logFAINC	-.1032706	.2938892	-0.35	0.726	-.6812932	.474752
SQR_NFAINC	.0033459	.0030069	1.11	0.267	-.0025681	.00926
SQR_DAIC	-.9342058	.2354638	-3.97	0.000	-1.397317	-.4710946
SQR_TLU	.8269059	.2247793	3.68	0.000	.384809	1.269003
_cons	-5.259482	3.780504	-1.39	0.165	-12.69499	2.176029
/sigma	1.872351	.1402121			1.596581	2.148121

```
  Obs. summary:        244  left-censored observations at intesit<=1
                       117     uncensored observations
                         0 right-censored observations
```

Appendix-7: Covariate balancing test

Variable	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduct |bias|	t-test t	t-test p>|t|	V(T)/ V(C)
logAge	U	3.62	3.7614	-55.5		-4.94	0.000	0.99
	M	3.6788	3.6805	-0.7	98.8	-0.05	0.958	0.89
SEXHH	U	.84615	.81557	8.1		0.71	0.475	.
	M	.85057	.8519	-0.4	95.7	-0.02	0.980	.
logFAMSIZ	U	1.8698	1.6484	62.7		5.34	0.000	0.60*
	M	1.826	1.8371	-3.2	95.0	-0.21	0.835	0.74
EDLE_HH	U	1.2051	.77459	63.3		5.81	0.000	1.43
	M	1.092	1.0862	0.8	98.7	0.05	0.957	1.06
TIMAI	U	.88889	.7418	38.5		3.25	0.001	.
	M	.86207	.85814	1.0	97.3	0.07	0.941	.
KWHTDCT	U	.92308	.82377	30.1		2.53	0.012	.
	M	.91954	.91252	2.1	92.9	0.17	0.868	.
PERCAI	U	.99145	.84836	54.5		4.24	0.000	.
	M	.98851	.97917	3.6	93.5	0.49	0.628	.
MOPHO	U	.66667	.47131	40.1		3.53	0.000	.
	M	.67816	.70768	-6.1	84.9	-0.42	0.675	.
ACGRLN	U	.83761	.62295	49.7		4.23	0.000	.
	M	.8046	.7934	2.6	94.8	0.18	0.855	.
logFAINC	U	10.107	10.091	3.7		0.34	0.736	1.32
	M	10.104	10.159	-12.4	-236.0	-0.80	0.426	1.57*
SQR_NFAINC	U	101.44	84.948	38.3		3.50	0.001	1.36
	M	93.492	93.393	0.2	99.4	0.02	0.987	1.52
SQR_DAIC	U	1.3837	1.7651	-64.7		-5.61	0.000	0.74
	M	1.4634	1.4882	-4.2	93.5	-0.30	0.763	1.30
SQR_TLU	U	3.7613	3.3159	71.9		6.30	0.000	0.84
	M	3.6685	3.6721	-0.6	99.2	-0.04	0.967	0.80

* if variance ratio outside [0.69; 1.44] for U and [0.65; 1.53] for M

Appendix-8: Chi-square test for the joint significance of variables

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.374	170.23	0.000	44.7	49.7	160.6*	0.57	14
Matched	0.006	1.39	1.000	2.9	2.1	17.8	1.66	14

* if B>25%, R outside [0.5; 2]

Appendix- 9: Joint significance test (likelihood ratio test)

M/Algorithms	Sample	Pseudo R^2	LRchi2	P>chi2	MeanBias	med bias	B
NN(1)	U	0.374	170.23	0.000	44.7	49.7	160.6
	M	0.052	12.48	0.489	11.8	9.0	53.9
NN(2)	U	0.374	170.23	0.000	44.7	49.7	160.6
	M	0.020	4.92	0.977	7.5	7.0	33.6
NN(3)	U	0.374	170.23	0.000	44.7	49.7	160.6
	M	0.011	2.65	0.999	5.4	4.0	24.6
NN(4)	U	0.374	170.23	0.000	44.7	49.7	160.6
	M	0.010	2.40	0.999	4.7	5.5	23.5
NN(5)	U	0.374	170.23	0.000	44.7	49.7	160.6
	M	0.006	1.53	1.000	3.6	3.6	18.7
Caliper (0.01)	U	0.374	170.23	0.000	44.7	49.7	160.6
	M	0.024	5.14	0.972	8.2	5.8	36.7
Caliper (0.25)	U	0.374	170.23	0.000	44.7	49.7	160.6
	M	0.027	6.49	0.926	7.9	8.7	37.8
Caliper (0.5)	U	0.374	170.23	0.000	44.7	49.7	160.6
	M	0.124	29.81	0.005	20.0	22.5	82.4
Kernel (0.1)	U	0.374	170.23	0.000	44.7	49.7	160.6
	M	0.006	1.39	1.000	2.9	2.1	17.8
Kernel (0.25)	U	0.374	170.23	0.000	44.7	49.7	160.6
	M	0.016	3.94	0.992	5.5	6.2	29.6
Kernel (0.5)	U	0.374	170.23	0.000	44.7	49.7	160.6
	M	0.071	17.22	0.189	14.5	14.9	62.0

Appendix 10: Result of average treatment effect on treated household

```
. rbounds ( SQR_LVSINC ) , gamma (1 (0.25) 3)

Rosenbaum bounds for SQR_LVSINC (N = 361 matched pairs)

Gamma           sig+      sig-    t-hat+    t-hat-       CI+       CI-
----------------------------------------------------------------------
    1              0         0   130.631   130.631   126.984   134.239
 1.25              0         0   127.275   133.967   123.543   137.606
  1.5              0         0   124.483   136.664   120.783   140.294
 1.75              0         0   122.201   138.945   118.489   142.696
    2              0         0   120.186   140.895   116.289    144.91
 2.25              0         0   118.545   142.593   114.473    146.71
  2.5              0         0   116.912   144.355   112.747    148.18
 2.75              0         0   115.546   145.757   111.144   149.811
    3              0         0    114.25   146.931   109.624    151.21

* gamma  - log odds of differential assignment due to unobserved factors
  sig+   - upper bound significance level
  sig-   - lower bound significance level
  t-hat+ - upper bound Hodges-Lehmann point estimate
  t-hat- - lower bound Hodges-Lehmann point estimate
  CI+    - upper bound confidence interval (a=  .95)
  CI-    - lower bound confidence interval (a=  .95)
```

Survey Questionnaire

Introduction: I am a student at Wolkite University conducting a master's thesis entitled "Impact of adopting artificial cattle insemination by small holder farmers on their well-being in case of Yem Special District" by collected the information about the impact of the technology on the wellbeing of the user. Please be free and provide genius response. All your responses are secured from consequences. All information will be used only for academic purposes.

General Instruction:- Please do not write your name simply answer your question by making a tick (✓) in the box and write in the space provided and for open ended questions.

Part I: - Socio-demographic background information

1. Sex of the household head male ☐ female ☐
2. Age of the household head (in number of year) __________
3. Marital status of the household head

Marred ☐ Single ☐ Divorced ☐ Widowed ☐

other specify______________________

4. Education level of the household head

Illiterate ☐ primary education ☐ Secondary education ☐

College education and above education ☐ other ☐

5. Do you have children? Yes ☐ No ☐
6. How many family members in your household?

	Age category	Number of persons		
		male	female	Total
1	<7			
2	7-14			
3	15-64			
4	>65			

Information on adoption and level of AI technology

1. Do you have awareness about Artificial Insemination service? Yes ☐

No ☐

2. If Q 1 answer is yes, how did you come to know about artificial insemination service? Extension agents ☐ my neighbors ☐

AI technicians ☐ Elders (community leaders) ☐

Other ______________________

3. When did you come to know about artificial insemination?(year) ________

4. Do you know the use of Artificial Insemination? Yes ☐ No ☐

5. If your answer to question number 4 is yes, specify the uses of AI? ______

6. Are you user of Artificial insemination service?Yes ☐ No ☐

7. If your answer for question number 6 is No, why? (Multiple answer possible)

No awareness ☐ Unavailability of technologies ☐

Cost of technologies ☐ not interested ☐

Lack of physically a well-qualified cow ☐ other specify

8. For how many years did you used artificial insemination service?________ Years.

9. Is there any constraint in adopting artificial insemination service? Yes ☐

No ☐

10. If your answer to Q9 is yes what are your constraints to use AI?

Specify______________

11. Do you have milk producing cows? Yes ☐ No ☐

12. How many cows are artificially inseminated you have? Specify in number _____

13. Do you own improved dairy breeds? Yes ☐ No ☐

14. If yes, which breeds?

Holstein ☐ Jersey ☐ Boran ☐

II. Economic Factors:-

Livestock types	Oxen	Cows	Heifer	Bull	Calves	Sheep	Goat	Chicken	Donkey	Horse	Mules	Others
Number												

1. What was your income in the previous year 2013 E.C?

Types of products		Produced in Qt	Value in birr	Types of products		Produced in Qt	Value in birr
	Tef				Papaya		
	Maize				Orange		
	Wheat				Avocado		
	Sorghum				Banana		
	Barley				Zeythun		
	Beans			**Fruit**	Mango		

1. What was your income from livestock and its products in the previous year 2013 E.C?

Income source		In number	Value in birr	Livestock sales	Leas / rent	Total income
Cattle	Oxen					
	Cows					
	Heifer					
	Bull					
	Calves					
Sheep and Goat	Sheep					
	Goat					
	Chicken					
Equine	Donkey					
	Horse					
	Mules					
Animal product	Milk in Lit.					
	Cheese in Kg					
	Butter inKg					
	Eggs in #					
	Honey in Kg					

2. What was your Non-farm income of the previous year 2013 E.C?

	Income in birr/year
Pensions	
Non-agricultural wage	
Self-employment in own businesses/ Home business	
Remittances	
Other	

1. What was your Agricultural input expenditure of the previous year 2013 E.C?

	Agricultural input	Amount purchased	Birr/Year
1	Fertilizer		
2	Chemical (like pesticide)		
3	Improved seed		
4	Irrigation		
5	Animal feed		
6	Inputs other than mentioned		

2. What was your Non-food Expenditure (Education, Medication, ceremonies) of the previous year 2013 E.C?

	Expenditures		Birr/Year
1	For education	Pen and pencil	
		Exercise books	
		Books	
		Uniform of school cloth	
		Education fee	
2	For Medication	For human (family members)	
		For animals	
3	For ceremonies (for social activity)	Edir	
		Equib	
		Accidents	
		Weeding	
		Other social ceremonies	
4	Sanitary and Utility Expenses for household	Cloth	
		Shoe	
		Soap	
		Cosmetics	
		Petroleum	
		For Power	

3. What was your Food expenditure of the previous year 2013 E.C ?

Type of food	Total expenditure for				Type of food	Total expenditure for			
	one month		one year (2013)			one month		one year (2013)	
	In Qt.	birr	Qt.	in birr		Qt.	birr	In Qt.	in birr
Crops					**Vegtables**				
Tef					Cabbage				
Maize					Tomatoes				
Wheat					Potatoes				
Sorghum					Keysir				
Barley					Karot				
Beans					Duba				
Oilseed					Shigurti				
Enset(kocho)					Other				
Godere/Casav									

III. Institutional Factors

1. Is an artificial insemination service available at the time when the cow is in heat (the period of sexual receptivity? Yes ☐ ☐ No
2. Is an AI service available on weekends & holidays?Yes ☐ No ☐

3. If your answer to the above question is no, what do you do?

   Pass the date without breeding the cow ☐ Use Natural Mating ☐

4. Do artificial insemination service providers come to your place to render the service? Yes ☐ No ☐

   5. If no, do you travel to service providers? Yes ☐ No ☐

   6. If your answer for question number 5 is no, why you don't have access to credit?

IV. Situational Factors

1. Do you know how to detect heat? Yes ☐ No ☐

2. If not how do you know the right time to inseminate?

AI technicians help me ☐ my neighbors help me in detecting heat ☐
My children help me in detecting heat ☐ other specify _________

3. How far is AI center from your home? Give you response in Km. ________

V. Behavioral Factors

1. What is your perception or understanding about the importance of AI?

Important ☐ Not important ☐

2. Do you think that the milk yield of artificially inseminated dairy cows is higher than the local ones? Yes ☐ No ☐

VI. Communication/information Factors

1. Do you have mobile phone? Yes ☐ No ☐

2. If yes, do you contact with AI technicians using your mobile phone?

Yes ☐ No ☐

3. If not how do you communicate with AI technicians?

I go to their office to communicate ☐ They come to My home regularly ☐
Other specify ____________________________

4. Do you participate in livestock management training? Yes ☐ No ☐

5. If yes can you mention the benefits you get from the training?_________________

VII. Social Factors

1. Do you know fellow (role model) farmers having a higher income and a better living standard, because they are users of artificial insemination? Yes ☐ No ☐

2. Do you participate in social activities like Equb,Edir ? Yes ☐ No ☐

3. Are you a social leader (Yesefer shimagle) Yes ☐ No ☐

4. If yes what is the importance of being a social leader?

It has no importance ☐ Very important for getting new information ☐

For getting a better income ☐ other specify___________________________

VIII. Farm Characteristics

1. Is there scarcity of feed for your animals? Yes ☐ No ☐
2. What are the major sources feed for your animals?

   Grazing land ☐ forage crops ☐

   Hay supplement ☐ other (specify) _____________

3. Do you get animal feed in the nearly markets? Yes ☐ No ☐

4. If yes, is it affordable (are you able to purchase)? Yes ☐ No ☐

5. Do you have access to grazing land? Yes ☐ No ☐

6. What is size of grazing land you own?___________ in hectare.

7. If no, do you use communal grazing land? Yes ☐ No ☐

8. Your source of water for your animals? Nearby river/lake ☐ Ponds ☐

Water pipe ☐ buying ☐ other specifies________________________

9. Do you get enough water for your animals? Yes ☐ No ☐

10. How many minutes hours does it take from your farm to water source?

11. Did you hire labor for your farm work? Yes ☐ No ☐

12. Do you sale milk, Butter, yogurt and cheese? Yes ☐ No ☐

For artificial insemination users only

1. Do you let your bull go along with the herd? Yes ☐ No ☐
2. Is an increase in your income after you start using artificial insemination service?

   Yes ☐ No ☐

3. If no, what is the reason? ____________________

4. What is the pattern/status/ of your milk income, livestock income and consumption after you started to use AI service? Increase ☐ the same ☐ decrease ☐ other______________

Checklists for Key Informants Interview (KII)

1. Do farmers participate in artificial insemination technology?
2. What are the constraints for the adoption of AI technologies?
3. What the community members involved in artificial insemination technologies (the rich/poor, female / male HHs, the literate/ illiterate, or other?)
4. Is the AI technology profitable to farmers after participating in the technology?
5. What are the changes/ improvements/ you observed the impacts on household's wellbeing status (households' income and consumption patter)?
6. Describe any social, economic and environmental problems in the district associated with AI technology adoption?

Check list for Focusing Group Discussion (FGD)

For extension agent

1. Did you know about household wellbeing concept?
2. What are the main constraints faced in the area during AI technology transfer?
3. How is the wellbeing status of the household in the study area?
4. Which method you prefer to transfer artificial insemination in the area?
5. Did you get an artificial insemination technology and wellbeing related training?

For sample households

1. What is your perception on the AI technologies?
2. How AI technology is difficult to adopt?
3. What kind of problem faced time of adopting AI technologies?

Thank You!!