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Yemane Hailu Gebre

Tigray Agricultural Research Institute, Humera, Tigray, Ethiopia

Gebrehiwot Weldegebrial Gebru

gebre2007@gmail.com

Mekelle University

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Barriers and Opportunities of Artificial Insemination Use in Dairy Cattle in Saesie-Tsaeda Emba District, Eastern Zone of Tigray, Ethiopia

Yemane Hailu Gebre^a, Gebrehiwot Weldegebrial Gebru^{1b},

^a Tigray Agricultural Research Institute, Humera, Tigray, Ethiopia

^b Department of Agricultural Economics and Rural Development, College of Dryland Agriculture and Natural Resources, Mekelle University, Mekelle, Tigray, Ethiopia

Abstract

This study assesses the barriers and opportunities of using Artificial Insemination (AI) technology for dairy cattle in Saesie-Tsaeda Emba District, Tigray, Ethiopia. We surveyed 204 households selected through systematic random sampling from two Kebeles, using face-to-face interviews, focus group discussions, and key informant interviews. Descriptive statistics, including frequencies and percentages, were employed to analyze the data. Key motivations for AI use include economic benefits like increased offspring market value and enhanced milk production. Practical factors such as service affordability, early pregnancy diagnosis, and reliable service provision also influence farmers' decisions. However, several constraints hinder AI adoption, including low pregnancy rates, challenges in heat detection, lack of awareness about AI benefits, communication issues, insufficient incentives for technicians, and accessibility problems. Addressing these constraints is essential for promoting AI technology among farmers. The government should create a supportive environment by focusing on improving pregnancy rates through better training, enhancing heat detection methods, raising awareness about AI benefits, improving stakeholder communication, and providing adequate incentives for technicians.

Keywords: Barriers, Opportunities, Artificial Insemination Technology, Saesie-Tsaeda Emba

1. Introduction

¹ Corresponding author's address: gebre2007@mail.com Mekelle University, Ethiopia.

Agriculture is the cornerstone of the Ethiopia's economy and primary sources of livelihood for its people (Tsehay et al., 2022), engaging 80% of the population and contributing 52% of the gross domestic product (GDP) and 90% of exports (Muluye, 2021; Tamene & Ashenafi, 2022; Yigezu Wendimu, 2021). It serves as primary livelihood for smallholder farmers. Within this sector, livestock plays a crucial role, accounting for approximately 12-16% national GDP and 30-35% of agricultural GDP, while supporting the livelihoods of 60-70% of the population (Endalew & Ayalew, 2016; Mekuriaw & Harris-Coble, 2021; Shapiro et al., 2017). Despite hosting over 59.5 million cattle—ranking first in Africa and sixth globally—Ethiopia's livestock productivity remains low due to factors such as inadequate management practices and poor genetic quality (Aklilu et al., 2018; Shiferaw et al., 2014).

To improve the cattle genetics, strategies like artificial insemination (AI) and the importation of exotic breeds have been adopted (Habtamu Lemma et al., 2010; Lemma et al., 2010; Worku & Alemayehu, 2016). However, the ideal conditions for raising exotic breeds are often unattainable on small farms. In contrast, indigenous breeds possess unique adaptations that enable them to thrive in local environments (Khainga, 2015). Crossbreeding these indigenous breeds with exotic ones can yield substantial benefits, with crossbred cattle producing up to four times more milk than local breeds (Duguma, 2020). Crossbreeding indigenous breeds with exotic ones can yield substantial benefits, with crossbred cattle producing up to four times more milk than local breeds (Duguma, 2020).

AI technology is a cost-effective method for enhancing genetic quality and has been available to dairy producers for many years. It can significantly boost milk production, with studies indicating that crossbred cattle can yield up to 1,500 liters annually, compared to 900 liters for pure Zebu (Temba, 2011). For AI to be successful, however, producers must carefully assess its advantages and limitations in their specific context. Understanding the constraints and opportunities related to AI technology is essential for stakeholders aiming to improve its effectiveness. This study seeks to identify and analyze the challenges and opportunities associated with AI technology use in the Saesie-Tsaeda Emba District of

Understanding the constraints and opportunities related to AI technology is essential for stakeholders aiming to improve its effectiveness. This study seeks to identify and analyze the challenges and opportunities associated with AI technology use in the Saesie-Tsaeda Emba District of Tigray, Ethiopia.

2. Methodology

2.1 Description of the Study Area

The study was conducted in the Saesie-Tsaeda Emba District, which is situated in the Eastern Zone of the Tigray region in northern Ethiopia. The district has 31,246 households and a total population of 139,191, comprising 65,796 men and 73,395 women. Of this population, 18,933 individuals (13.60%) reside in urban areas. Regarding farming practices, approximately 69.31% of farmers engage in both crop and livestock production, whereas 26.28% focus solely on crop production and 4.41% depend exclusively on livestock rearing. According to a 2018 annual report from the Office of Agricultural and Rural Development (OoARD), cited by (Gebre et al., 2022), the estimated total livestock population in the district includes 98,276 cattle (90,990 local and 7,286 hybrid), 124,997 sheep, 46,950 goats, 15,577 donkeys, 96 horses, 33 mules, and 6 camels.

2.2 Sample Size Determination and Sampling Procedure

This research used a survey design and a three-stage sampling technique were employed to select the study sites and sample households. The sample size was calculated using Yemane's formula (1967, cited (Yamane, 1973)) to reduce errors and biases in the selection process. Applied at a 95% confidence interval, the formula is as follows:

$$n = \frac{N}{1 + N(e)^2} = \frac{1,798}{1 + 1,798(0.066)^2} \approx 204$$
 sample households were chosen using systematic random sampling (Table 1:).

Where:

- 82 n = sample size drawn from the total households
- 83 N = total number of household heads in the two peasant associations (1,798)
- 84 e = margin of error tolerance (0.066)
- 85 1 = probability of the event occurring

86 **Table 1: Sample distribution of milk producers**

Number	Name of Sample kebeles (Peasant associations)		
	Sinkata	Hadush-hiwot	Total
Total population	947	851	1798
Sample households	107	97	204

87 **2.3 Types, Sources, and Methods of Data Collection**

88 An interview schedule was developed, pre-tested, and validated. To ensure accurate
89 responses, questions were administered in the appropriate local language. The validity
90 and reliability of the schedule were assessed through a pre-test with 20 respondents prior
91 to the main survey, and necessary adjustments were based on the preliminary findings.

92 Farmers were asked to provide information on their socioeconomic characteristics and to
93 identify the key constraints and opportunities associated with the use of artificial
94 insemination technology.

95 Data were collected using a two-part instrument. The first part covered demographic and
96 socioeconomic variables, including age, education, family size, livestock holdings,
97 distance to market, distance to farmer training center (FTC), distance to the AI
98 technician's office, gender, training attendance, access to extension services, and mobile
99 phone ownership.

100 The second part focused on the major constraints and opportunities related to AI services.
101 Respondents were asked to rank these factors according to their significance and
102 influence.

Furthermore, the survey data were complemented with data collected from key informant interviewees (KII) and focus group discussants (FGDs) sample households. The combination of the key informants and focus group discussants for the study in AI technology adoption were designed to be methodologically sound, contextually relevant, and feasible given the post-conflict recovery context in Tigray (2023-2026). In total 40 sample key informants' interviews and two FGDs were conducted to cross-check the reliability and validity of the qualitative data analysis which is crucial to give context-based conclusion and recommendation.

2.4 Method of Data Analysis

This study employed both descriptive and inferential statistical methods. Descriptive statistics-specifically frequencies, percentages, and arithmetic means were used to summarize the data and present findings.

To test the hypotheses related to the research variables, chi-square and t-test were applied. The chi-square test was used for dummy or categorical variables, while the t-test was employed to determine statistically significant differences between the means of continuous variables when comparing AI technology users and non-users across qualitative characteristics.

The main constraints and opportunities associated with AI technology adoption were identified and ranked using the ranking index method, following the approach described by (Musa et al., 2006; Musa, 2006).

$$\text{Ranking index} = \frac{R_n + (R_n - 1) * C_2 + \dots + R_n * C_n}{\sum R_n * C_1 + (R_n - 1) * C_2 + \dots + R_1 * C_n}$$

Where, R_n =Value given for the least level ranked (in this case, for example, in constraints the least rank is 7th, then $R_n=7$, $R_n-1=6$, $R_n=1$) and C_n = Counts of the least ranked level (in our case, the count of the 7th rank= C_n , and the count of the 1st rank= C_1).

3. Results and Discussions

3.1 Demographic and socioeconomic characteristics of sample KIIs and FGDs

3.1.1 Descriptive Results for Continuous Variables

Table 2 provides important insights into the characteristics of respondents in relation to the adoption of AI technology for hybrid cattle. Of the 204 respondents, only 23.5 were identified as AI technology users, while the vast majority (76.5%) were non-users. This significant disparity highlights a key concern for agricultural extension services and policymakers seeking to enhance livestock productivity through modern breeding methods

Table 2: Descriptive Statistics for Continuous Variables

Continuous variables	Respondents (N=204)				t- test
	AI technology users (48)		AI technology non-users (156)		
	Mean	Std. Dev	Mean	Std. Dev.	
Age of household heads	50.15	6.75	51.92	11.83	0.99
Family Size	6.31	1.87	5.14	2.11	-3.45
Land Size	.48	.19	.55	.30	1.39
Total livestock holding in TLU	5.50	2.06	5.15	1.20	-1.51
Distance to FTC	41.25	6.15	48.56	9.87	4.84
Distance to AI Officer	35.63	6.49	42.30	8.92	4.80

Regarding demographic characteristics, the average age of AI technology users (50.15 years) and non-users (51.92 years) did not differ in a significant way. This suggests that age may not be a critical determinant of AI adoption within this sample population.

In contrast, a notable difference emerged in family size. AI users had an average of 6.31 members per household, compared to 5.14 members among non-users. This finding implies that larger households may be more inclined to adopt new technologies, possibly due to the greater availability of labor to manage the additional responsibilities associated with AI.

The results Table 2 depicted that landholding size did not differ significantly between AI users and non-users, with average of 0.48 hectares for users and 0.55 hectares for non-users. This suggests that landholding size alone may not be a major determinant of AI adoption decisions. Likewise, livestock holding size, measured in Tropical Livestock Unit (TLU), showed no significant difference between the two groups-users averaged 5.51

TLU, while non-users averaged 5.15 TLU. This indicates that the capacity to manage livestock does not necessarily correlate with the adoption of AI technology.

In contrast, significant differences emerged regarding distances to both the Farmer Training Center (FTC) and the AI inseminator's office. AI users lived closer to FTCs (averaging 41.25 minutes) than non-users (48.56 minutes), and also closer to AI service stations (35.63 minutes versus 42.29 minutes for non-users). These findings highlight that proximity to resources and support services plays a crucial role in facilitating AI adoption. This result aligns with existing literature emphasizing the importance of accessibility to agricultural in promoting technology adoption among farmers.

3.1.2 Descriptive Results for Discrete Variables

Table 3: Descriptive Results for Discrete Variables

Variable name	Attribute	Respondents (N=204)		
		AI technology users (48)	AI technology non- users (156)	Chi-square (χ^2)
Sex of the household head	Male	64.56%	71.79%	0.9107
	Female	35.42%	28.21%	
Literacy level of the household head	Illiterate	6.25%	21.15%	5.6102
	Literate	93.75%	78.85%	
Access to Training	Untrained	14.58%	63.46%	35.1313
	Trained	85.42%	36.54%	
Feed supplementation Practice	No	50%	86.54%	9.7623
	Yes	50%	13.46%	
Mobile phone ownership	No	29.17%	71.15%	27.2704
	Yes	70.83%	28.85%	
Extension contact with developmental agents	No	16.67%	53.85%	20.4926
	Yes	83.33%	46.15%	

Table 3 presents the results for discrete variables and highlights several key factors influencing AI technology adoption among farmers. The demographic analysis shows that male respondents constituted 70.10% of the total sample. Specifically, 64.56% of AI users and 71.79% of non-users came from male-headed households. However, the Pearson chi-square test revealed no significant association between the sex of the household head and AI usage ($\chi^2 = 0.9107$). This suggests that gender is not a critical determinant of AI

adoption, as both male and female-headed households appear to face similar opportunities and barriers.

Literacy level significantly influenced AI adoption. Overall, 82.35% of households were literate; however, a notable gap existed between AI users (93.75% literate) and non-users (78.85 literate). This difference was statistically significant at the 1% level ($\chi^2 = 5.6102$), emphasizing the role of education in promoting technology adoption. Literate individuals may have better access to information and resources needed to understand and implement AI technology.

Training in livestock production also proved crucial. While 48.04% of all respondents had received training, the contrast between users (85.42% trained) and non-users (36.54 trained) was striking. Chi-square analysis confirmed a significant relationship at the 1% level ($\chi^2 = 35.1313$), highlighting the need for targeted training programs to equip farmers with the skills required for advanced technologies like AI.

Supplementary feeding practices were generally low, with only 22.06% of respondents providing additional feed to their cattle. However, a significant difference emerged between AI users (50%) and non-users (13.46%). the chi-square statistic ($\chi^2 = 30.674$) indicates a strong association between supplementary feeding and AI adoption, suggesting that farmers who invest in feeding practices are more committed to improving livestock health and productivity, making them more likely to adopt AI.

Mobile phone access also significantly influenced AI use. Among AI users, 70.83% owned mobile phones, compared to only 28.85% of non-users. The chi-square value ($\chi^2 = 27.2704$) confirms a significant difference, indicating that AI users are more likely to leverage mobile technology to access AI-related information and services.

Finally, contact with development agents (DAs) emerged as an important determinant of AI adoption. Approximately 54.90% of farmers reported contact with DAs, with a clear distinction between AI users (83.33%) and non-users (46.15%). Chi-square analysis ($\chi^2 = 20.4926$) revealed a statistically significant difference, underscoring the critical role of extension services in facilitating technology adoption.

3.2 Barriers to AI Technology Adoption among Farmers

The survey identified several significant concerns that hinder the adoption of AI technology among farmers. These barriers range from technical challenges related to reproductive management to institutional factors such as weak extension services and technical incentives. Detailed analysis of the major barriers Table 4 ranked by the percentage of the respondent's response are provided here under.

Results of the survey analysis revealed that the most prominent barrier to AI technology adoption was poor pregnancy rates, identified by 22.06% of the sample respondents. Low conception rates undermine farmers' confidence in AI, leading them to prefer traditional natural mating methods, which they perceive as more reliable. This is similar with previous studies by (Abigaba et al., 2022; Omondi et al., 2017). To address this concern, the FGDs and key informants pinpointed AI technicians require continuous training to improve insemination skills; semen quality must be ensured through poor collection, handling, and storage protocols; and it is essential to implement better reproductive management practices to increase conception rates and rebuild farmers trust in AI technology. This intervention recommendations from the respondents is aligned with previous studies by (Abigaba et al., 2022; Mendizabal-Ruiz et al., 2025).

Additionally, accurate heat detection is a vital for successful AI implementation. However, 19.42% of participants identified heat detection as a critical barrier. It is true that many farmers struggle to identify the optimal time for insemination, which directly impacts conception rates (Mekuriaw & Harris-Coble, 2021). Inline to this, the key informants depicted that training programs that educate farmers on effective heat detection methods and technologies could help alleviate this barrier.

Furthermore, a significant lack of awareness about AI's benefits was cited by 15.34% of respondents as a barrier to adoption. Many farmers do not fully understand how AI can enhance genetic potential, improve herd productivity, or increase profitability compared to traditional breeding methods. This knowledge gap is compounded by communication challenges, also depicted by 15.34% of the sample participants. Effective communication between farmers and technicians is crucial for successful AI implementation, as

misunderstandings or insufficient information can lead to improper timing, missed insemination opportunities, and ultimately, low conception rates (Kashoma & Ngou, 2023b; Tawfik & Al-Hamdany, 2025). Improving communication channels and fostering stronger relationships between farmers and service providers can enhance collaboration. The key informants and the FGDs underlined intervention of improving communication through mobile phones, community meetings, and demonstration events, and fostering stronger relationship between farmers and service providers could enhance adoption of AI in a sustainable way. Also, identified the role of agricultural extension services a particular role for making practical here for the aforementioned interventions.

Additionally, insufficient incentives for technicians, identified by 12.80% of respondents, play a crucial role in the adoption of AI technology. Inadequately incentivized technicians affect negatively their commitment in promoting AI technology. Offering better compensation, training, and support could encourage technicians to actively engage with farmers and promote AI practices. The findings of this study are consistent with previous studies by (Arowosegbe et al., 2024; Melesse et al., 2020b).

Moreover, the short time frame for effective insemination, noted by 9.16% of farmers, complicates the adoption process. Farmers may feel pressured or unable to coordinate insemination within this limited timeframe, leading to frustration and a preference for natural mating. Geographic or logistical accessibility issues, mentioned by 5.90% of respondents, can also limit farmers' access to AI services. Addressing these challenges through mobile services or community-based approaches could facilitate greater adoption.

Key informants confirmed that the primary reasons for preferring natural mating or not adopting AI technology include limited knowledge about AI, late reporting, poor communication, and accessibility problems. These findings align with those of (Kashoma & Ngou, 2023a; Nadarzynski et al., 2021; Nicholson, 1999).

250 **Table 4: Barriers for not using AI technology**

Barriers	Responses, N=204	1 st (7 marks)	2 nd (6 marks)	3 rd (5 marks)	4 th (4 marks)	5 th (3 marks)	6 th (2 marks)	7 th (1 mark)	Total	Index	Rank	Interventions recommend d by FGD and KII to enhance adoption of AI by farmers
Heat detection Problem	Freq.	26	82	51	45	0	0	0	204	0.194153	2 nd	Farmer training on estrus signs; use of heat detection aids
	Weight	182	492	255	180	0	0	0	1109			
Poor pregnancy Rate	Freq.	115	36	27	26	0	0	0	204	0.220588	1 st	Improve semen quality; train technicians, enhance reproductive management
	Weight	805	216	135	104	0	0	0	1260			
Short time of heat	Freq.	0	0	26	0	82	51	45	204	0.091562	5 th	Education on estrus timing; fixed-time AI where feasible
	Weight	0	0	130	0	246	102	45	523			
Communication Problem	Freq.	27	0	91	0	60	26	0	204	0.153361	3 rd	Mobile phone-based communication; community meetings; stronger extension worker-farmer linkages
	Weight	189	0	455	0	180	52	0	876			
Lack of incentive for the technicians	Freq.	0	26	9	78	36	55	0	204	0.127976	4 th	Performance-based pay; logistical support; regular training
	Weight	0	156	45	312	108	110	0	731			
Not accessible	Freq.	0	9	0	0	26	36	133	204	0.058999	6 th	Mobile AI services; community-based technicians
	Weight	182	492	255	180	0	0	0	337			
Lack of awareness	Freq.	36	51	0	55	0	36	26	204	0.153361	3 rd	Extension campaigns; demonstration events; farmer-to-farmer learning
	Weight	252	306	0	220	0	72	26	876			
Total										1.00		

3.3 Opportunities to AI Technology Adoption among Farmers

The survey findings offer valuable insights into the motivations driving household to adopt AI technology in dairy cattle production. Understanding these motivations is essential for developing strategies to increase AI adoption rates among farmers. As summarized in Table 5, factors influence farmers' decisions to adopt AI, ranging from economic benefits to institutional support.

The data revealed that the high market value of AI offspring was the most significant motivator, accounting for 18.41% of the weighted response. This was followed by increased milk production potential (15.98%), low cost of AI services (13.96%), early pregnancy diagnosis (13.35%), reliable and quality service (12.95%), extension officer prioritization (12.88%), and introduction of zero grazing (12.47). These findings align with previous studies by (Mekuriaw et al., 2019; Nath et al., 2025; Quddus, 2012; Valbuena et al., 2015a) (Table 5).

It is found that higher market value of AI offspring (index: 0.1841) ranked as the primary motivational factor for AI adoption was the highest market value of AI-generated offspring, identified by 18.41% of respondents. Farmers recognized that AI, when used with genetically superior semen, can produce calves with improved growth rates, diseases resistance, and conformation traits (Quddus, 2012). The superior command better prices in local and regional markets, directly impacting profitability, and long-term sustainability.

Additionally, the finding suggests that farmers are not merely subsistence-oriented but also responsive to market signals. Interventions that demonstrate the economic returns of AI-bred calves through market linkages, premium pricing could further incentivize adoption (Nath et al., 2025).

Increased milk production (index: 0.1598) has also found as the second ranked most potential motivation factor (15.98%) for increased milk production from dairy cow farmers. Farmers view enhanced herd productivity as a direct pathway to greater income and improved livelihood. AI enables access to high-genetic-merit sires known for milk yield, butterfat content, and lactation length (Pastrana et al., 2026; Rabel et al., 2024; Valbuena

et al., 2015b). this motivation is particularly relevant for smallholder dairy farmers who depend on milk sales for daily cash income. However, realizing this potential requires complementary investments in nutrition, health care, and management. Simply providing AI without addressing feed quality or veterinary services may lead to disappointment and reduced trust (Mekuriaw et al., 2019). Similarly, previous studies from South Asia and East Africa have consistently shown that perceived productivity gains are among the strongest predictors of AI adoption (Nath et al., 2025; Quddus, 2012).

Low cost of AI services (Index: 0.1396): It found ranked 3rd motivational factor for adoption of AI technology among smallholder dairy farmers. The affordability of AI services relative to natural mating was found to increase motivation farmers AI adoption by 13.96%. maintaining a bull involves significant costs such as feed, health care, housing, and the risk of injury or aggression. AI eliminates these recurring expenses while providing access to superior genetics at a fraction of costs. The results of this study are consistent with previous studies by (Dixit et al., 2024; Kacew et al., 2021; Shen et al., 2024). In addition, price sensitivity is high among smallholder farmers. Subsidizing AI services or bundling packages could further lower perceived barriers but sustainability of AI adoption requires that farmers eventually bear full costs once benefits are demonstrated (Mekuriaw & Harris-Coble, 2021).

Early pregnancy diagnosis (Index: 0.1335): The survey result revealed 13.35% of the sample farmers found motivated to adopt AI due to its attractive feature to diagnosis pregnancy at an early stage. They noted as AI program enables farmers make informed herd management decisions. The Focus group discussants and key informants also confirmed that early confirmation pregnancy allows farmers to avoid unnecessary re-breeding attempts, identify non-pregnant cows for timely re-insemination or culling, optimize feed and resource allocation cycles, and plan calving and milk production cycles. The farmers also experienced as early pregnancy diagnosis reduces calving interval and increases lifetime productivity of dairy cows.

Reliable, quality, and regular service (Index: 0.1295): The study results revealed that assurance of reliable, high-quality, and consistent AI services was cited by 12.95% and

ranked as 5th motivational factor by the sample respondents. Trust in service providers significantly influences adoption decisions. Farmers are more likely to use AI when they are confident that technicians will arrive on time, that semen has been properly stored, and that conception outcomes will be acceptable (Mekuriaw et al., 2019; Mekuriaw & Harris-Coble, 2021). It is also consistent with the study by (Oloo et al., 2023; Ssekibaala et al., 2025) founds programs that invest in technician certifications, performance monitoring, and customer feedback mechanisms to achieve higher adoption rates that enhance reliable and quality service functions.

Similarly, Extension officers provide priority to AI technology (Index: 0.1288): Results of the study also revealed that extension officers provide priority to AI was found to have crucial role and rank 6th by 12.88% of the sample respondents in enhancing farmers opportunity in adoption of AI utilization in dairy cattle. The FGDs and key informants' interviewee complement the results of the survey that agricultural (livestock) extension workers play a crucial role in educating farmers about AI's benefits, demonstrating proper techniques, and providing follow-up support. Results of this study is aligns previous study by (Melesse et al., 2020a). Similarly, the key informant interviewees confirmed that the influence of extension workers is particularly important in areas where farmer awareness is low. Also, revealed when extension workers consistently recommend AI and facilitate access to services, farmers perceive AI as a valid and trustworthy technology. Conversely, they are clearly assured extension workers who lack training and motivation influences negatively to the adoption of AI by farmers.

Introduction to zero grazing practices (0.1247): This was the least but not the last not ranked by 12.47% of the respondent farmers depicted that introduction of zero grazing or confined feeding systems plays significant role in Adoption of AI among smallholder farmers. Despite its least ranking by the farmers, it remains relevant. The finding is consistent with the previous studies by (Mee & Boyle, 2020; Nendissa et al., 2023; Valbuena et al., 2015b; Wróbel et al., 2023), who stated zero grazing where cattle are kept in enclosures and fed cut forage; and it optimizes land use, reduces environmental degradation, and improves animal welfare.

Overall, each AI adoption opportunity corresponds to a specific constraint requiring policy action. The higher market value of offspring is undermined by poor pregnancy rates, necessitating improved conception rates to realize genetic potential. Increased milk production is limited by lack of awareness, calling for training link AI to productivity gains. The low cost of AI services is offset by insufficient technician incentives; saving from bull maintenance should be reallocated to technician compensation. Early pregnancy diagnosis is hindered by heat detection problems, suggesting that heat detection raining be bundled with pregnancy diagnosis services. Reliable service is constrained by accessibility challenges, requiring investment in mobile or community-based service delivery. Extension prioritization faces communication issues, highlighting the need to strengthen development agents (DA) training and farmer-extension linkages. Finally, zero grazing introduction is constrained by the short heat window, recommending that zero grazing be combined with fixed-time AI protocols.

351 **Table 5:** Reasons for adopting AI technology

352

List of Opportunities	Responses; N=204	1 st (7 marks)	2 nd (6)	3 rd (5)	4 th (4)	5 th (3)	6 th (2)	7 th (1 mark)	Total	Index	Rank
Higher market value of AI offspring	Freq.	19	13	5	5	5	1	0	48	0.184086	1 st
	Weight	133	78	25	20	15	2	0	273		
AI increases the milk production potential of dairy cows	Freq.	15	8	6	5	6	8	0	48	0.159811	2 nd
	Weight	105	48	30	20	18	16	0	237		
Pregnancy diagnosis at an early stage	Freq.	8	8	6	6	6	8	6	48	0.133513	4 th
	Weight	56	48	30	24	18	16	6	198		
Low cost of the service	Freq.	9	7	12	3	2	9	6	48	0.139582	3 rd
	Weight	63	42	60	12	6	18	6	207		
Introduction of zero grazing	Freq.	3	7	12	5	6	9	6	48	0.124747	7 th
	Weight	21	42	60	20	18	18	6	185		
Extension officers provide priority to AI technology	Freq.	5	7	12	3	6	9	6	48	0.128793	6 th
	Weight	35	42	60	12	18	18	6	191		
Get reliable, quality, and regular service	Freq.	4	7	11	7	6	8	5	48	0.129467	5 th
	Weight	28	42	55	28	18	16	5	192		
Total										1.00	

4. Conclusions and Recommendations

Although AI technology in dairy breeding remains underutilized it plays a crucial role in improving farmers' livelihoods through enhanced genetic potential, increased milk production, and higher offspring value. However, AI adoption is hampered by various social, economic, and institutional factors specific to the local context.

While socioeconomic factors such as age and landholding size do not significantly impact AI adoption, several other factors do. These include: family size, literacy levels, training attendance, supplementary feeding practices, and mobile phone access. Besides, proximity to FTCs and AI service points were identified as the most geographic factor whereas frequency of extension contacts with agricultural extension workers and technician incentives, and communication quality accessibility issues were identified among the major factors affecting AI technology adoption among smallholder farmers.

Furthermore, results of the ranking data analysis pinpointed the primary reasons for not using AI or preferring natural mating include low pregnancy rates, heat detection challenges, lack of awareness about AI's benefits, communication barriers, inadequate technician incentives, the short heat window, and accessibility issues.

Conversely, the main drivers of AI adoption include the higher market value of AI offspring, increased milk production potential, low service costs, early pregnancy diagnosis, reliable service delivery, extension officer support, and complementary practices such as zero grazing.

Overall, to improve AI technology adoption among farmers, a comprehensive strategy involving concerned governmental and non-governmental organizations is essential. Accordingly, authors recommend the following actions:

1. Improve pregnancy rates: enhancing technician training, implement regular training, and ensure consistent supply of quality semen.
2. Strengthen heat detection: provide detection aids, integrate training into extension programs, and explore fixed-time AI protocols.

3. Increase awareness and communication: conduct demonstration events, use mobile phones and radio, and strengthen farmer-technician communication.
4. Enhance technical incentives: offers performance-based compensation, logistical support, regular training, and recognition for high performers.
5. Improve accessibility: deploy mobile AI units, train community-based technicians, and coordinate services with market days or community meetings.
6. Leverage extension services: train development agents on AI, integrate AI into extension programs, and establish farmer: extension-technician feedback loops.
7. Promote complementary practices: encourage zero grazing, provide training on nutrition and record-keeping, and link AI adoption to credit or feed input packages.

Abbreviations

AI: Artificial insemination; **KII:** Key informants' interview; **FGD:** Focus group discussion

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Author contributions

All the authors significantly contributed to the overall development of this manuscript. Yemane Hailu Gebre: Conceptualization, methodology, data collection, and writing the original draft. Gebrehiwot Weldegebrial Gebru: Methodological design, qualitative analysis and interpretation of its results, and reviewing the manuscript. Both the authors have read, agreed, and approved to the final version of the manuscript.

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Data availability

The datasets generated during and /or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate

The study received written ethical approval from Mekelle University's Research and Community Services Directorate (RCSD) Ethics Committee (reference number, MU-RCSD-124/24. All research procedures were performed in accordance with the ethical guidelines and regulations of Mekelle University and the principles outlined in the declarations of Helsinki.

Consent for publication

Not applicable.

Consent to participate

Informed consent was obtained from all the participants prior to their involvement in the study. Due to high rates of the illiteracy among the study population, verbal informed consent was sought and obtained instead of written consent. Before providing consent, participants were fully informed about the study's purpose, potential risks, and their right to withdraw at any time without penalty. The voluntary nature of their participation was emphasized. Verbal consent was documented via audio recording using mobile phones of the trained enumerators. Confidentiality and anonymity were strictly maintained regarding participant identities.

Field permission

The authors were granted an official letter of fieldwork household survey permission from the local authority office prior to formal data collection started.

Competing interest

The authors declare no competing interests.

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