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Assessing Stakeholder Engagement in the Unified National Artificial Insemination Program for Cattle in Negros Oriental: Awareness, Challenges, and Support Systems

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Abstract. This study addresses the knowledge gap regarding farmer awareness, inseminator challenges, and institutional support systems in the implementation of the UNAIP cattle artificial insemination program in Negros Oriental. Employing a descriptive-correlational research design, with a random sample of 298 farmers and a census of 52 inseminators, data were collected through expert-validated questionnaires and analyzed using means, standard deviations, and Spearman's rank correlation. Results reveal that farmers exhibit a very high level of awareness about AI benefits and procedures, influenced by experience, education, and cultural perceptions. At the same time, inseminators face multiple logistical and technical challenges. Institutional support is generally rated as adequate; however, logistical constraints and support responsiveness vary across regions. Key findings include a lack of significant correlation between support systems and AI success rates, suggesting biological, environmental, and farmer-driven factors are critical for success. The study concludes that a comprehensive, community-driven approach is necessary to enhance AI adoption and program effectiveness, contributing valuable insights for policymakers and stakeholders to improve livestock development in rural areas.

Keywords: Artificial insemination; Farmer awareness; Inseminator support; Livestock development; Negros Oriental; UNAIP.

1.0 Introduction

Adopting artificial insemination (AI) is widely recognized as a critical strategy for improving livestock productivity, enhancing genetic quality, and reducing disease transmission risks (Valdez, 2024). Across the globe, AI has been successfully implemented to boost meat and dairy production, contributing to food security and rural development. However, despite its demonstrated benefits, AI adoption in the Philippines—particularly in Negros Oriental—remains inconsistent and uneven, limiting its potential impact on local cattle farming communities.

The Philippine government, through the Department of Agriculture, has institutionalized the Unified National Artificial Insemination Program (UNAIP) to promote AI as a national strategy for livestock improvement (Department of Agriculture, 2023). However, in provinces like Negros Oriental, AI adoption faces persistent challenges, including low farmer engagement, inconsistent success rates, and limited program sustainability. These issues are often attributed to socio-institutional factors such as inadequate farmer knowledge, cultural perceptions that influence technology acceptance, and the responsiveness of institutional support systems—factors that remain underexplored in local research.

While several studies have highlighted the technical and economic barriers to AI adoption (Abella et al., 2017; Chandran et al., 2025), limited literature examines how social, cultural, and institutional dynamics shape program outcomes at the grassroots level. Existing works identify logistical constraints, cultural resistance, and technical challenges as key barriers (Soriano et al., 2021; Latonio et al., 2019), yet these findings are not fully contextualized within the specific realities of Negros Oriental. For instance, the province's geographic diversity—spanning upland, lowland, and coastal areas—compounds logistical difficulties, while varying cultural beliefs and farmer practices influence the acceptance and implementation of AI services. Moreover, inseminators face operational limitations such as insufficient access to materials like lubricants and liquid nitrogen, poor mobility support, and reactive rather than proactive institutional assistance.

This study seeks to address these gaps by assessing the levels of awareness among cattle farmers, identifying the challenges faced by artificial inseminators, and evaluating the adequacy of institutional support under UNAIP in Negros Oriental. By examining these socio-institutional factors, the research aims to develop a nuanced understanding of the barriers and enablers of AI adoption in the province. The findings will provide actionable insights to guide policymakers, livestock program implementers, and development partners in crafting more inclusive, responsive, and community-driven strategies to enhance AI adoption and improve livestock productivity. Ultimately, this study contributes to advancing rural development goals, particularly those related to food security, sustainable agricultural practices, and livelihood improvement in Philippine farming communities, in alignment with the Sustainable Development Goals (SDGs) on Zero Hunger, Quality Education, Industry, Innovation and Infrastructure, and Responsible Consumption and Production.

2.0 Methodology

2.1 Research Design

This study utilized a descriptive-correlational research design, which was appropriate for examining both the current state and the interrelationships among key variables within the context of the UNAIP in Negros Oriental. Specifically, the descriptive component aimed to present a clear picture of farmers' awareness levels regarding the benefits and procedures of artificial insemination and the extent of challenges and support systems experienced by AI technicians. Meanwhile, the correlational component sought to determine the existence and strength of relationships among these variables, such as the association between farmer awareness and demographic factors, and the relationship between the level of support provided to inseminators and their challenges. The findings from this approach helped clarify the socio-technical dynamics that influenced the success of UNAIP implementation at the grassroots level.

2.2 Research Locale

The research was conducted in selected LGUs across the three legislative districts of Negros Oriental. To ensure representativeness and contextual relevance, the study targeted the top three LGUs per district, based on AI service records from 2021 to 2023, provided by the PVO. These LGUs include Ayungon, Guihulngan City, and Manjuyod for District 1; Tanjay City, Dumaguete City, and Pamplona for District 2; and Bayawan City, Bacong, and Zamboanguita for District 3. These LGUs were chosen to reflect both performance and diversity regarding agricultural practices, logistical support, and implementation outcomes of the UNAIP. By selecting LGUs with the most active AI programs, the research environment captured areas with a functioning AI delivery system, offering rich insights into best practices and persistent challenges. Additionally, this geographical distribution allowed the study to analyze the effects of farmer awareness, inseminator challenges, and support systems across the province's varying socio-economic and agro-ecological conditions. This approach not only strengthened the relevance and accuracy of the findings but also supported the formulation of targeted, evidence-based recommendations for program improvement.

2.3 Research Participants

This study involved two respondent groups: farmers and artificial inseminators. For the farmers, the researcher employed a performance-based selection of municipalities, focusing on the top three AI-performing LGUs per district based on PVO AI service records from 2021 to 2023. These LGUs include Ayungon, Guihulngan City, and Manjuyod for District 1; Tanjay City, Dumaguete City, and Pamplona for District 2; and Bayawan City, Bacong, and Zamboanguita for District 3. Within these LGUs, the pool of eligible respondents consisted of RSBSA-registered cattle farmers owning at least one breedable cow as of May 15, 2024, based on DA-RFO 7 records. The minimum sample size was computed using the RAOSOFT online calculator at a 90% confidence level, 5% margin of error, and 50% population proportion, resulting in a required sample of 267 farmers. The final number of farmer-respondents was increased to 298 to enhance reliability and account for potential non-responses.

Simple random sampling was employed within each selected LGU. A master list of qualified farmers was randomized using a random number generator, ensuring that each farmer had an equal and independent chance of selection. This approach guaranteed proportional representation across municipalities based on their respective cattle farming populations. Meanwhile, the researcher adopted a census approach for artificial inseminators. Given their manageable population size and critical role in AI service delivery, all 52 registered inseminators under the PVO of Negros Oriental were included. This inclusion allowed for comprehensive data collection regarding inseminators' support systems, challenges, and professional profiles. The farmer respondents varied by age, educational attainment, years of farming experience, and geographic setting (lowland, upland, coastal, rural, urban), providing a broad representation of the cattle-farming community. Inseminators likewise varied by educational background, years of AI practice, and skill development levels, contributing rich insights into the operational realities under UNAIP.

2.4 Research Instrument

The researcher developed two structured survey questionnaires for cattle farmers and one for artificial inseminators to collect primary data. Each instrument was designed to address the study's objective, which is to gauge farmer awareness and inseminator challenges and support systems under the UNAIP in Negros Oriental. The farmers' questionnaire was translated into Cebuano to ensure respondent comprehension, while the inseminators' questionnaire was worded in English due to its technical content and the intended respondents' professional background. The first part of the questionnaire consists of a disclosure statement, which outlines the study's purpose: to evaluate the effectiveness of UNAIP from the farmers' perspective. The disclosure statement underscores the voluntary nature of participation, ensures confidentiality, and emphasizes that the data collected will be used strictly for academic purposes. It also verifies that the completion of the survey is considered evidence of informed consent, which is in line with ethical research standards. The second part gathers demographic information, including age, gender, civil status, educational attainment, farming and cattle raising experience, current herd size, and geographic location (e.g., upland, lowland, coastal, urban, or rural). It also contains questions regarding cultural perceptions that may have influenced farmers' views on artificial insemination, such as traditional beliefs and community norms. The third part measures farmers' awareness of the UNAIP. This includes items related to their understanding of the program's benefits, such as improved genetics, increased productivity, reduced breeding costs, and disease control, and their knowledge of AI procedures, including estrus detection, insemination timing, proper animal preparation, and post-care. Responses are rated using a 5-point Likert scale, from 1 (Unaware) to 5 (Very Aware). The fourth part evaluates the extent of support received from UNAIP, including access to AI services and materials, training opportunities, financial assistance, and technical support. Each item is evaluated on a scale from 1 to 5, where 1 represents "Inadequate" and 5 signifies "Very Adequate." This section concludes with an open-ended question to gather suggestions and recommendations from respondents.

For the artificial inseminators' questionnaire: The first part includes a disclosure statement similar to that in the farmer version, presenting the study's objectives, confidentiality measures, and ethical guidelines. The respondent's completion of the survey serves as informed consent. The second part collects demographic data such as age, gender, civil status, educational level, years of experience as an inseminator, and a self-assessed skill rating (from novice to expert). This provides contextual background to interpret the responses better. The third part measures the extent of support received in two key areas: (1) equipment and storage facilities, such as AI guns, liquid nitrogen tanks, and semen storage rooms; and (2) professional development opportunities, including training, access to information on AI updates, and peer collaboration. Responses are rated using a 5-point scale from 1 (Inadequate) to 5 (Very Adequate). The fourth part addresses the challenges experienced by inseminators in delivering services, including poor cow nutrition, farmer cooperation, logistical barriers, low-quality semen, and heat detection issues. It also asks respondents to rate their perceived AI success rate and indicate whether they receive any incentives based on service performance. Frequency scales ranging from 1 (Never) to 5 (Always) are used.

Instrument reliability and pilot testing. Before the study was fully implemented, a dry run or pilot test was conducted to assess the research instruments' clarity, consistency, and reliability. A total of 30 farmers and 5 artificial inseminators participated in the dry run. Cronbach's Alpha was computed separately to evaluate the instruments' internal consistency. The farmers' questionnaire yielded an alpha value of 0.9244, while the inseminators' questionnaire recorded 0.9202. According to Tavakol and Dennick (2011), alpha values above 0.90 indicated excellent internal consistency, confirming that both instruments are reliable and valid for field administration. In addition to statistical validation, the instruments underwent review and validation by three experts: an agricultural field expert, a professional statistician, and a member of the academe. Their comments and suggestions ensured the instruments' content validity, technical soundness, and contextual relevance, strengthening the credibility of the research process. With a well-structured design, strong reliability scores, and expert validation, the research instruments provided a sound foundation for gathering accurate, relevant, consistent data supporting the study's objectives.

2.5 Data Gathering Procedure

After the design hearing, the researcher incorporated all recommended revisions and secured formal approval to conduct the study through a letter endorsed by the Dean of the Graduate School of Foundation University. The Provincial Veterinary Office (PVO) and relevant LGUs in the selected municipalities granted this approval. Following approval, the researcher worked with livestock technicians to generate master lists of eligible respondents. A simple random sampling method was used to select 298 farmers from the RSBSA-listed cattle owners based on a sample size calculation at a 90% confidence level and 5% margin of error. Additional respondents were included to account for possible non-responses. Meanwhile, all 52 registered artificial inseminators were included using a census approach, ensuring full population coverage. Coordination with the Provincial Veterinarian, District Livestock Program Coordinators, and the Provincial Artificial Insemination Coordinator was conducted to organize orientation sessions and briefings with stakeholders. These sessions explained the study's objectives, ethical safeguards, and expected outcomes to secure their cooperation.

Data collection was conducted face-to-face from March to April 2025. Participants completed expert-validated questionnaires after a short orientation on voluntary participation and confidentiality. To ensure completeness, questionnaires were collected immediately after completion. Before full deployment, the questionnaire underwent pilot testing with 30 respondents to ensure clarity and reliability. Minor revisions were made based on pilot feedback. To evaluate internal consistency, Cronbach's Alpha was calculated separately for each instrument. The farmers' questionnaire yielded an alpha coefficient of 0.9244, and the inseminators' questionnaire recorded 0.9202, indicating excellent reliability based on commonly accepted statistical standards. Collected data were encoded in Microsoft Excel and analyzed using Megastat and SPSS software. Descriptive statistics (frequency, percentage, mean, standard deviation) summarized demographic profiles and key variables. At the same time, Spearman's rank-order correlation tested the relationships between farmer demographics, awareness levels, support systems, and inseminator challenges. All tests were conducted at a 0.05 level of significance.

2.6 Data Analysis Procedure

Data collected from the respondents were encoded, processed, and analyzed using Microsoft Excel and SPSS software. Descriptive and inferential statistical methods were applied to address the study objectives and test the hypotheses. Frequency and percentage were used to present the demographic profiles of cattle farmers and artificial inseminators, including age, education level, geographic location, years of experience, and cultural perceptions. Mean and standard deviation were used to determine the extent of farmers' awareness of the benefits and procedures of the UNAIP, the level of institutional support received by inseminators in terms of equipment, storage facilities, and professional development, and the extent of challenges they experienced related to service delivery and AI success rates.

Spearman's rank-order correlation coefficient was employed to examine relationships between variables. This test was specifically applied to determine the relationship between farmers' awareness levels and their demographic characteristics, addressing Objective 2 and testing Hypothesis 1 (H_{01}). It was also used to evaluate the relationship between the extent of support received by inseminators and the challenges they experienced in service delivery and success rates, addressing Objective 5 and testing Hypothesis 2 (H_{02}). Spearman's correlation was selected to analyze relationships involving ordinal or ranked data derived from Likert-scale responses. All statistical analyses were performed at a 0.05 level of significance, meaning relationships were considered statistically significant if the p-value was less than or equal to 0.05. These analyses provided the basis for interpreting farmer awareness levels, inseminator challenges, institutional support, and the interrelationships among these factors.

2.7 Ethical Considerations

This study complied with ethical research standards to protect participants' rights, privacy, and well-being. Ethical approval was secured from the Foundation University Graduate School Ethics Committee. The PVO and the relevant LGUs in the selected municipalities also authorized the study. Prior to data collection, all participants were provided with clear information about the study's objectives, voluntary nature, confidentiality measures, and their right to withdraw at any time without consequence. Written informed consent was obtained from all participants before administering the survey. No personally identifiable information was collected, and all responses were used solely for academic and research purposes.

3.0 Results and Discussion

3.1 Extent of Farmers' Awareness on the UNAIP in Negros Oriental in terms of the Benefits of AI

Table 1 reveals that farmers in Negros Oriental have a "very high" level of awareness of the benefits of AI, as indicated by a composite weighted mean of 4.47 (SD = 0.76). Among the specific indicators, farmers demonstrated the highest awareness of AI's role in improving the genetic quality of livestock ($\bar{x}$ = 4.63, SD = 0.66), followed by its contribution to faster herd improvement ($\bar{x}$ = 4.50, SD = 0.72). These findings suggest that farmers are well-informed about the core advantages of AI in livestock production, particularly in enhancing breed quality and productivity.

Table 1. *Extent of Farmers' Awareness on the UNAIP in Negros Oriental in terms of the Benefits of AI (n = 298)*

Indicator	$\bar{x}$	SD	VD	EoA
1. Improved genetic quality of livestock	4.63	0.66	VA	VH
2. Faster herd improvement	4.50	0.72	VA	VH
3. Increased milk/meat production	4.47	0.80	VA	VH
4. Reduced disease transmission	4.38	0.77	VA	VH
5. Reduced cost of breeding	4.37	0.83	VA	VH
Composite	**4.47**	**0.76**	**VA**	**VH**

Note: Verbal Description (VD); Extent of Awareness (EoA); 1.00-1.80, Unaware (U), Very Low (VL); 1.81-2.60, Slightly Aware (SA), Low (L); 2.61-3.40, Moderately Aware (MA), Moderate (M); 3.41-4.20, Aware (A), High (H); 4.21-5.00, Very Aware (VA), Very High (VH)

This result aligns with the study of Latonio et al. (2019), which emphasized that improved genetics is a key benefit of AI in cattle and goat farming systems, contributing to increased conception rates and enhanced animal performance. Similarly, Valdez (2024) posited that using AI leads to genetic improvements that result in better growth rates, higher milk yields, and superior meat quality—factors that farmers recognize. These insights also align with the systematic review by Seth et al. (2025), which highlighted that farmers are more likely to adopt AI when they perceive direct benefits in herd quality and income generation. However, the practical implications of this high awareness deserve closer examination. While farmers report understanding the benefits, the province still faces uneven AI adoption and variable success rates, suggesting that awareness alone cannot improve program outcomes. This calls for a strategic shift from awareness-raising to skill-building, particularly in technical aspects like estrus detection, insemination timing, and post-AI care, often the critical failure points in AI success.

These findings are especially relevant for program implementers and agricultural extension workers. While the high awareness level among farmers is encouraging, it must be translated into accurate and consistent practice. Future interventions should therefore prioritize procedural training and reinforce hands-on skills through practical demonstrations, on-farm mentoring, and peer-led learning models tailored to local contexts. Moreover, the intense awareness reported by farmers reinforces the importance of sustaining and expanding government efforts under the UNAIP. The Department of Agriculture (2023) notes that farmer engagement is closely linked to their perceived economic benefits. Continued investments in localized extension, structured incentive programs, and support infrastructure will be crucial to ensure that farmers are informed and empowered to adopt AI effectively.

Lastly, because awareness does not always translate into behavioral change, future program evaluations should include performance-based metrics such as actual AI adoption rates, conception success rates, and farmer satisfaction. Additionally, follow-up assessments should be conducted to measure knowledge retention and field-level application of AI practices. These strategies are essential for bridging the gap between knowledge and implementation, thereby improving AI outcomes at the farm level and ensuring the long-term success of the UNAIP in Negros Oriental.

3.2 Extent of Farmers' Awareness on the UNAIP in Negros Oriental in terms of the Procedures of AI

Table 2 illustrates that farmers in Negros Oriental exhibit a "very high" level of awareness of the specific procedures involved in AI, as reflected by the overall weighted mean of 4.40 (SD = 0.84). Among the procedural aspects, the highest level of awareness was observed in the proper preparation of livestock prior to insemination ($\bar{x}$ = 4.54, SD = 0.74), followed by correct handling and maintenance of AI equipment and materials ($\bar{x}$ = 4.46, SD = 0.84), and the provision of post-insemination care ($\bar{x}$ = 4.44, SD = 0.81). These results indicate that farmers are well-informed about the core steps for successful AI application.

Table 2. *Extent of Farmers' Awareness on the UNAIP in Negros Oriental in terms of the Procedures of AI (n=298)*

Indicator	$\bar{x}$	VD	EoA	SD
1. Livestock must be prepared well for AI	4.54	VA	VH	0.74
2. AI equipment and materials must be properly maintained	4.46	VA	VH	0.84
3. Proper post-insemination care must be provided	4.44	VA	VH	0.81
4. Estrus must be accurately detected before proceeding with AI	4.41	VA	VH	0.85
5. Insemination events must be accurately recorded	4.37	VA	VH	0.87
6. Insemination must follow the optimal timing (AM–PM rule)	4.30	VA	VH	0.84
Composite	**4.40**	**VA**	**VH**	**0.84**

Note: Verbal Description (VD); Extent of Awareness (EoA); 1.00-1.80, Unaware (U), Very Low (VL); 1.81-2.60, Slightly Aware (SA), Low (L); 2.61-3.40, Moderately Aware (MA), Moderate (M); 3.41-4.20, Aware (A), High (H); 4.21-5.00, Very Aware (VA), Very High (VH)

These findings suggest that farmers recognize the procedural requirements necessary for AI success. However, the slightly lower ratings for estrus detection and proper record-keeping, while still classified as "very high," warrant attention. As Latonio et al. (2019) noted, these aspects are among the most critical and commonly overlooked steps influencing conception success. Failure to detect heat accurately or mistiming insemination can significantly reduce AI success rates, even when farmers are generally aware of AI procedures. This observation raises concerns that reported awareness may not fully translate into accurate practice. Some farmers may overstate their understanding or misinterpret procedural steps, particularly in timing-sensitive tasks like heat detection and AM–PM rule adherence. This highlights a potential performance gap between what farmers know in theory and what they apply in practice. Such gaps have been identified by Soriano et al. (2021) and Ybañez et al. (2017), who stressed that technical precision and proper animal condition are critical to AI success but are often undermined by field-level errors or misunderstandings.

While the high awareness levels are encouraging, these results should not be overinterpreted as a guarantee of procedural competency. Awareness is only the first step; consistent practice, demonstration-based learning, and field monitoring are necessary to ensure that farmers know what to do and perform procedures correctly and consistently. Seth et al. (2025) support this, emphasizing that procedural knowledge must be reinforced by continuous learning and institutional support to drive technology adoption and program sustainability. Moreover, the importance of accurate record-keeping cannot be overstated. Proper documentation is essential for monitoring reproductive performance, evaluating program outcomes, and qualifying for government incentives like the AICCI program (Department of Agriculture, 2023). Farmers who fail to maintain records may miss out on support programs and reduce AI services' accountability in their communities.

The slightly lower awareness of the AM–PM rule, which guides the optimal timing of insemination, further underlines the need for targeted training on heat detection and insemination timing. Latonio et al. (2019) identified poor heat detection as one of the leading causes of AI failure in smallholder systems, making this a priority area for intervention. Strengthening farmers' ability to recognize signs of estrus and correctly apply timing protocols could significantly improve conception outcomes. Overall, while the high procedural awareness reported by farmers provides a solid foundation for strengthening AI implementation, these findings also reveal specific areas for improvement, particularly in estrus detection, insemination timing, and record-keeping. Extension services and training programs should shift focus from general awareness-raising to practical, skills-based capacity-building that enables farmers to apply these procedures confidently and accurately in real-world conditions. Monitoring and follow-up support will be essential to sustain improvements and ensure that procedural knowledge is effectively translated into practice, thereby maximizing the impact of UNAIP in Negros Oriental.

3.3 Relationship between Farmers' Demographic Profile and Their Awareness of AI Benefits

Table 3 presents the relationship between farmers' demographic characteristics and their awareness of AI's benefits under UNAIP. Using Spearman's Rank-Order Correlation at a 0.05 level of significance, the results show that years of farming experience (0.114, p = 0.048) and cultural perception (0.276, p = 0.028) were significantly correlated with awareness of AI benefits. Conversely, no significant relationships were found between farmers' awareness and age, education level, or geographic location.

Table 3. *Relationship between Farmers' Demographic Profile and Their Awareness of AI Benefits (n = 298)*

Demographic Variable	Computed Value	p	Decision	Remark
Educational Level	$r_s = 0.104$	0.338	Fail to reject H_o	Not significant
Age	$r_s = 0.093$	0.108	Fail to reject H_o	Not significant
Years of Farming Experience	$r_s = 0.114$	0.048	Reject H_o	Significant
Geographic Location	$r_{pbi} = 0.121$	0.132	Fail to reject H_o	Not significant
Cultural Perception (Y/N)	$r_{pbi} = 0.276$	0.028	Reject H_o	Significant

Note: Between ± 0.50 to ± 1.00 (strong); ± 0.30 to ± 0.49 (moderate); ± 0.10 to ± 0.29 (weak); ± 0.01 to ± 0.09 (very weak)

While the strength of these correlations is relatively weak, the statistical significance suggests that practical experience and cultural alignment contribute meaningfully to farmers' understanding of AI benefits. Specifically, the positive relationship with farming experience implies that hands-on exposure over time helps farmers better appreciate the genetic and productivity gains that AI offers. This supports Valdez (2024), who noted that long-term engagement in livestock production increases openness to adopting reproductive technologies, especially when farmers witness observable improvements in herd quality and productivity. Interestingly, cultural perception showed a stronger correlation compared to other factors, highlighting the positive role of local beliefs and practices in shaping farmers' attitudes toward AI. Contrary to common assumptions that cultural traditions may hinder the adoption of modern technologies, this finding suggests that when AI is framed as compatible with local values, it becomes more acceptable to farmers. This aligns with Peralta (2024), who emphasized that culturally responsive extension strategies increase community receptiveness to livestock innovations. Farmers who view AI as a tool for improving animal health, securing household income, or fulfilling community expectations are likelier to engage with the technology.

Conversely, the lack of significant relationships with education level and age is somewhat counterintuitive. One might expect that more formally educated or younger farmers would show higher awareness. However, this result suggests that formal education alone does not guarantee practical understanding, nor does generational status automatically translate to increased openness to AI. This highlights the limitation of relying solely on classroom-based learning or targeting specific age groups without providing practical, field-based learning opportunities. Israel and Briones (2013) and Chandran et al. (2025) similarly argued that behavioral change in rural contexts is driven more by experiential learning, peer influence, and social proof than by demographic characteristics alone.

Supporting this view, Edale (2025) documented that AI programs integrating community-based interventions and cultural practices achieved higher success rates among smallholder farmers. Foote (2002) also historically emphasized that respecting local traditions was critical in the global diffusion of AI technologies. This reinforces the idea that cultural alignment should not be viewed as a barrier but a strategic lever for adoption. Moreover, these findings align with Valencia et al. (2023) and Pingali et al. (2021), who stressed that addressing socio-psychological drivers, such as trust, pride, and cultural affirmation, can accelerate technology adoption, particularly among traditional or risk-averse farming communities. Overall, these results signify that farming experience and cultural context are key drivers of AI awareness, and that UNAIP implementation should leverage these insights to tailor communication strategies. Efforts incorporating culturally grounded messaging and highlighting real-life success stories from experienced farmers may enhance the impact of awareness campaigns more effectively than general demographic targeting alone.

3.4 Relationship between Farmers' Demographic Profile and Their Awareness of AI Procedures

Table 4 presents the relationship between farmers' demographic characteristics and their awareness of AI procedures under the UNAIP. Using Spearman's Rank-Order Correlation at a 0.05 level of significance, the findings show that education level (0.198, p = 0.010) and cultural perception (0.301, p = 0.016) have significant relationships with awareness of AI procedures. Geographic location yielded a marginally significant result (0.165, p = 0.054), while age (–0.034, p = 0.562) and years of farming experience (0.018, p = 0.753) showed no significant correlation.

Table 4. *Relationship between Farmers' Demographic Profile and Their Awareness of AI Procedures (n = 298)*

Demographic Variable	Computed Value	p	Decision	Remark
Years of Farming Experience	$r_s = 0.018$	0.753	Fail to reject H_o	Not significant
Age	$r_s = -0.034$	0.562	Fail to reject H_o	Not significant
Education Level	$r_s = 0.198$	0.010	Reject H_o	Significant
Geographic Location	$r_{pbi} = 0.165$	0.054	Fail to reject H_o	Not significant
Cultural Perception (Y/N)	$r_{pbi} = 0.301$	0.016	Reject H_o	Significant

Note: Between ± 0.50 to ± 1.00 (strong); ± 0.30 to ± 0.49 (moderate); ± 0.10 to ± 0.29 (weak); ± 0.01 to ± 0.09 (very weak)

The results imply that awareness of AI procedures is shaped more by educational attainment and cultural alignment than by age or experience alone. The significant relationship with education suggests that formal schooling enhances the ability to comprehend the technical steps involved in AI, such as estrus detection, proper timing, and equipment handling. Correspondingly, Israel and Briones (2013) postulated that higher education levels are positively associated with the understanding and adopting agricultural innovations, especially when technical knowledge is required. Likewise, cultural perception significantly influenced procedural awareness. Farmers who acknowledged cultural or traditional beliefs regarding livestock practices were likelier to demonstrate higher awareness of AI procedures. This finding reflects Peralta's (2024) assertion that local values can facilitate technology adoption rather than barriers when respected and integrated into program messaging. Farmers may perceive AI as an extension of their animal care and breeding beliefs, increasing acceptance when culturally resonant explanations are used.

Interestingly, geographic location approached significance, suggesting that access to information and extension services may differ slightly between rural, upland, and lowland communities. Soriano et al. (2021) observed that logistical barriers in GIDAs can lead to unequal exposure to technical training, potentially affecting awareness levels in procedural topics that require step-by-step understanding. This is echoed by Tadesse et al. (2022), who found that poor extension coverage contributes to procedural errors in AI delivery and suboptimal success rates. Conversely, no significant relationship was found between age or years of farming experience and awareness of AI procedures, contrasting with the findings on AI benefits. This suggests that experience alone may not be sufficient to build procedural competence, especially for a technique like AI that requires specific training. While older and more experienced farmers may recognize the value of AI, they may not necessarily understand the precise timing or practices involved unless directly taught.

This finding reinforces the conclusions of Toledo et al. (2019), who observed that generational status alone does not predict the correct application of AI methods. Instead, continuous learning opportunities and access to updated technical practices are more decisive in shaping procedural awareness than age or farming tenure. The findings suggest that a farmer's technical awareness of AI procedures relies more on formal education and culturally responsive training approaches than on years of farming experience alone. As such, UNAIP implementers should tailor procedural training to local belief systems and deliver it in formats accessible to farmers with lower education levels, such as visual demonstrations or peer-led sessions. This approach aligns with Valdez's (2024) statement that translating technical knowledge into community practice requires grounding it in culturally familiar terms and participatory formats.

3.5 Support Received by the Artificial Inseminators in terms of Equipment and Storage Facilities

Table 5 presents the perceived extent of support received by artificial inseminators in Negros Oriental regarding equipment and storage facilities. Findings indicate that the overall level of support is considered "adequate," as reflected by a composite mean of 3.43 (SD = 1.33). This suggests that, generally, inseminators have reasonable access to the core resources necessary to perform their duties under the UNAIP. Among the items evaluated, the most adequately supported indicators were the availability of AI guns and gloves (both $\bar{x}$ = 3.96), followed closely by sheaths ($\bar{x}$ = 3.94) and record-keeping systems ($\bar{x}$ = 3.94). These results reflect that inseminators are well-equipped with the standard tools required for hygienic and efficient insemination procedures. Soriano et al. (2021) reported that the availability of essential AI equipment significantly enhances the accuracy, safety, and overall success of insemination services. Furthermore, the provision of reliable documentation systems aligns with the findings of Ybañez et al. (2017), who emphasized that consistent record-keeping is critical in monitoring reproductive outcomes and ensuring technician eligibility for performance-based incentives like the AICCI program.

Table 5. *Support Received by the Artificial Inseminators in terms of Equipment and Storage Facilities (n=52)*

Indicator	$\bar{x}$	VD	EoS	SD
1. AI Guns	3.96	A	H	1.41
2. Gloves	3.96	A	H	1.37
3. Sheaths	3.94	A	H	1.39
4. Record-Keeping System	3.94	A	H	0.87
5. Liquid Nitrogen Tank	3.58	A	H	1.38
6. AI Laboratory	3.58	A	H	1.36
7. Semen Storage Room	3.48	A	H	1.42
8. Canisters and Canes	3.42	A	H	1.49
9. Lubricant	2.40	SA	L	1.29
10. Liquid Nitrogen Plant	2.08	SA	L	1.30
Composite	**3.43**	**A**	**H**	**1.33**

Note: Verbal Description (VD); Extent of Support (EoS); 1.00-1.80, Inadequate (I), Very Low (VL); 1.81-2.60, Slightly Adequate (SA), Low (L); 2.61-3.40, Moderately Adequate (MA), Moderate (M); 3.41-4.20, Adequate (A), High (H); 4.21-5.00, Very Adequate (VA), Very High (VH)

In contrast, lubricant availability ($\bar{x}$ = 2.40) and access to liquid nitrogen plants ($\bar{x}$ = 2.08) were perceived as only "slightly adequate." These relatively lower ratings point to weaknesses in the cold chain infrastructure, an essential component in maintaining semen viability during storage and transport. This finding reflects concerns Valdez (2024) raised, who identified the lack of localized liquid nitrogen supply as a persistent challenge in sustaining AI operations, particularly in geographically isolated or upland municipalities. The findings mirror those of Tadesse et al. (2022), who found that disruptions in cold chain supply significantly reduce AI effectiveness and raise the likelihood of failed conception.

These logistical gaps are especially concerning given that semen quality is time- and temperature-sensitive. According to Abella et al. (2017) and Peña and Lañada (2019), any delay or improper semen storage can compromise the entire insemination process. Patel et al. (2017) also stressed the importance of functional AI laboratories and cold storage units in ensuring reproductive biotechnology outcomes, particularly in developing contexts. Briones (2020) and Toledo et al. (2019) similarly emphasized that even with trained personnel, AI service delivery cannot succeed without complementary infrastructure support. These findings underscore the urgent need to improve cold chain logistics by investing in mobile nitrogen delivery units, establishing partnerships with regional liquid nitrogen suppliers, and supporting the development of community-managed AI storage hubs, particularly in underserved municipalities. Edale (2025) reported that regions integrating technical support with logistics enhancement have demonstrated greater AI diffusion and farmer engagement.

International studies also echo this concern. For instance, Zuidema et al. (2021) and Chandran et al. (2025) stressed that without robust logistical and equipment support, AI programs face structural limits that no technician training alone can overcome. Seth et al. (2025) further argue that comprehensive institutional support ensures operational effectiveness and long-term sustainability in livestock genetic improvement efforts. Overall, while inseminators in Negros Oriental are adequately supplied with basic AI tools, the weaknesses in lubricant availability and liquid nitrogen access pose significant operational risks. Addressing these gaps requires strategic investments in cold chain logistics and infrastructure, without which the province's AI services will continue to face inconsistencies in service delivery and reproductive outcomes. Strengthening these logistical systems is critical for ensuring that inseminators can perform their roles effectively, thereby improving the overall impact and sustainability of UNAIP in Negros Oriental.

3.6 Support Received by Artificial Inseminators in terms of Professional Development

Table 6 shows the extent of professional development support as perceived by artificial inseminators in Negros Oriental. Based on the overall rating, the extent of professional development support is "adequate," with a composite mean of 3.83 (SD = 0.96), suggesting that inseminators generally have access to training and technical learning opportunities essential for their fieldwork.

Table 6. *Support Received by Artificial Inseminators in terms of Professional Development (n=52)*

Indicator	$\bar{x}$	VD	EoS	SD
1. Availability of training programs	4.04	A	H	0.91
2. Interaction with experienced inseminators	3.90	A	H	0.75
3. Access to information on AI advancements	3.56	A	H	1.23
Composite	**3.83**	**A**	**H**	**0.96**

Note: Verbal Description (VD); Extent of Support (EoS); 1.00-1.80, Inadequate (I), Very Low (VL); 1.81-2.60, Slightly Adequate (SA), Low (L); 2.61-3.40, Moderately Adequate (MA), Moderate (M); 3.41-4.20, Adequate (A), High (H); 4.21-5.00, Very Adequate (VA), Very High (VH)

Among the indicators, the highest-rated was the availability of training programs ($\bar{x}$ = 4.04, SD = 0.91), followed closely by interaction with experienced inseminators ($\bar{x}$ = 3.90, SD = 0.75). These findings indicate that institutional partners such as the PVO, the DA, and national agencies like the PCC and the NDA have played a significant role in technical capacity-building for inseminators. This supports the conclusions of Soriano et al. (2021), who posited that regular training is essential for improving procedural accuracy, particularly in semen handling, estrus detection, and service delivery efficiency. The strong rating for peer interaction further reflects the value of informal mentorship in the field. As Valdez (2024) noted, practical learning through collaboration with more experienced technicians enhances real-time problem-solving, boosts field confidence, and ensures the transfer of best practices, particularly in rural areas where access to formal education or institutional workshops may be limited. However, the lowest-rated item was access to updated information on AI advancements ($\bar{x}$ = 3.56, SD = 1.23). While still within the "adequate" category, this relatively lower score suggests a gap in the flow of scientific and technical updates to the field level. This concern is echoed by Briones (2020), who observed that frontline agricultural service providers often lack exposure to the latest technologies, innovations, and protocols due to limitations in digital access, the absence of continuing education systems, or weak coordination between research and extension services.

The findings imply that while existing training structures are functional and beneficial, the UNAIP would benefit from institutionalizing ongoing learning platforms such as refresher courses, mobile-based updates, or field demonstrations of new technologies. These approaches would allow inseminators to stay current with modern AI practices and maintain a high standard of service. Enhancing digital connectivity and offering access to e-learning modules could also address the identified information access gap. Overall, the data confirm that inseminators in the province are well-supported in professional development, particularly in foundational training and peer-based learning. However, ensuring consistent exposure to technological advancements and research-based improvements in AI protocols remains essential for improving field-level effectiveness and sustaining long-term program outcomes under the UNAIP.

3.7 Challenges Experienced by Artificial Inseminators in terms of Quality of Service Delivery

Table 7 illustrates the challenges encountered by artificial inseminators concerning the quality of AI service delivery in Negros Oriental. The data show an overall "sometimes" level of occurrence, with a composite mean of 3.01 (SD = 1.07). This suggests that while inseminators can generally carry out their duties, they face intermittent barriers affecting service outcomes.

Table 7. *Challenges Experienced by Artificial Inseminators in terms of Quality of Service Delivery (n=52)*

Indicator	$\bar{x}$	VD	EoC	SD
1. Farmers' lack of awareness about estrus detection, cow nutrition, and post-insemination care	3.31	S	M	1.04
2. Difficulty in reaching farmers in remote areas	3.14	S	M	1.03
3. Farmers' indifferent behavior towards AI	3.10	S	M	0.96
4. Limited access to AI materials and equipment	3.08	S	M	0.99
5. Insufficient supply or accessibility of liquid nitrogen	3.04	S	M	1.10
6. Inadequate training in AI procedures	2.40	R	L	1.33
Composite	**3.01**	**S**	**M**	**1.07**

Note: Verbal Description (VD); Extent of Challenges (EoC); 1.00-1.80, Never (N), Very Low (VL); 1.81-2.60, Rare (R), Low (L); 2.61-3.40, Sometimes (S), Moderate (M); 3.41-4.20, Frequent (F), High (H); 4.21-5.00, Always (A), Very High (VH)

Among the most frequently experienced challenges is farmers' lack of awareness of estrus detection, cow nutrition, and post-insemination care ($\bar{x}$ = 3.31). This means that despite the technical competence of inseminators, gaps in farmer knowledge continue to hinder the success of AI procedures. These findings strengthen the statement of Soriano et al. (2021) that the effectiveness of insemination is closely linked to farmer cooperation and understanding of reproductive management. Without accurate heat detection and adequate animal care from the farmer, even well-executed insemination efforts may fail to result in conception. Other moderately rated challenges include difficulty reaching remote areas ($\bar{x}$ = 3.14) and farmer indifference or lack of cooperation ($\bar{x}$ = 3.10). These data expose the logistical and behavioral barriers that inseminators continue to face, particularly in GIDAs. Similarly, Briones (2020) noted that field technicians deployed in upland and remote barangays often delay providing timely services due to poor transportation infrastructure and distance. Although the mean score for mobility-related challenges falls within the "sometimes" range (2.61–3.40), a mean of 3.14 is relatively close to the higher end of the scale, indicating that mobility difficulties are moderately frequent.

In this study, inseminators also reported specific mobility-related concerns, such as the absence of dedicated service vehicles, lack of fuel subsidies, and the need to shoulder transportation expenses to reach remote farms personally. While these mobility constraints do not occur daily, they happen often enough to disrupt the timeliness and consistency of AI service delivery, particularly during the critical estrus period when insemination must be promptly conducted within a narrow window of 12-18 hours. Even occasional delays can lead to failed conception, financial losses for farmers, and frustration toward AI services. Literature affirms that logistical delays, even when occasional, undermine AI success rates and technician morale (Briones, 2020; Soriano et al., 2021). Moreover, the personal financial burden of covering transport costs further demotivates inseminators and threatens the sustainability of service delivery, especially in GIDAs. These findings underline the urgent need to strengthen mobility support systems, such as the provision of motorcycles, fuel allowances, or transportation subsidies, to enhance field service efficiency and ensure equitable AI access for all cattle farmers.

Operational limitations were also observed. Challenges like limited AI materials and equipment access ($\bar{x}$ = 3.08) and occasional liquid nitrogen shortages ($\bar{x}$ = 3.04) reveal gaps in the support systems essential to maintaining AI operations. These findings align with those of Valdez (2024), who found that interruptions in cold chain logistics, especially during high-demand periods, significantly impact the ability of inseminators to meet service expectations. The least reported concern was inadequate training in AI procedures ($\bar{x}$ = 2.40), suggesting that inseminators generally feel confident and well-prepared regarding technical competence. This supports the positive impact of ongoing training and mentoring facilitated by the PVO and institutional partners like the Agricultural Training Institute (ATI). As posited by Ybañez et al. (2017), well-structured refresher sessions and peer learning have proven effective in enhancing the competence and consistency of field technicians.

These findings imply that while inseminators are generally skilled and supported in their role, external challenges such as farmer awareness gaps, rugged terrain, and logistical shortfalls still constrain the complete success of AI service delivery. To address these limitations, the UNAIP must invest in farmer education programs, especially those focused on reproductive management and animal health. At the same time, greater logistical support, such as transportation assistance and improved cold chain systems, should be provided to inseminators working in hard-to-reach communities. The challenges faced by inseminators in Negros Oriental reflect a broader need to improve both the supply and demand sides of AI services. Strengthening institutional support for ongoing professional development, enhancing digital and field-based learning mechanisms, and improving research-extension linkages are essential policy directions to sustain and elevate UNAIP's impact in the province and beyond.

3.8 Challenges Experienced by Artificial Inseminators in terms of Success Rate

Table 8 outlines the challenges artificial inseminators encounter concerning the success rate of insemination outcomes under the UNAIP. The findings indicate an overall rating of "sometimes" experienced, with a composite mean of 2.67 (SD = 1.00). This means that while AI-related challenges are not consistently present, they occur often enough to impact conception outcomes across the province. High environmental stress is the most commonly cited concern ($\bar{x}$ = 3.29, SD = 0.98), followed by poor cow nutrition and body condition ($\bar{x}$ = 3.15, SD = 0.85). These ratings emphasize that biological and climatic conditions are central to AI success. Soriano et al. (2021) argued that heat stress due to elevated temperatures can impair estrus detection, disrupt hormonal balance, and reduce fertility. These complications directly affect the timing and outcome of AI procedures. Similarly, Valdez (2024) stressed the importance of animal nutritional status during insemination, explaining that cows in suboptimal body condition are less likely to ovulate regularly or sustain early pregnancies.

Table 8. *Challenges Experienced by Artificial Inseminators in terms of Success Rate (n=52)*

Indicator	$\bar{x}$	VD	EoC	SD
1. High environmental stress	3.29	S	M	0.98
2. Poor cow nutrition and body condition	3.15	S	M	0.85
3. Poor record-keeping and farm management	2.71	S	M	0.87
4. Cost and accessibility of AI materials and services	2.67	S	M	0.99
5. Difficulty in detecting heat	2.56	S	M	1.07
6. Poor timing of insemination	2.52	S	M	1.08
7. Low-quality semen or improper semen handling	2.39	R	L	1.01
8. Lack of proper training or AI technique errors	2.10	R	L	1.13
Composite	**2.67**	**S**	**M**	**1.00**

Note: Verbal Description (VD); Extent of Challenges (EoC); 1.00-1.80, Never (N), Very Low (VL); 1.81-2.60, Rare (R), Low (L); 2.61-3.40, Sometimes (S), Moderate (M); 3.41-4.20, Frequent (F), High (H); 4.21-5.00, Always (A), Very High (VH)

In addition, farm-level operational challenges were reported at moderate levels. These include inefficient record-keeping and farm management practices ($\bar{x}$ = 2.71) and issues surrounding the cost and accessibility of AI materials and services ($\bar{x}$ = 2.67). Such constraints point to weaknesses in reproductive planning and herd monitoring systems. As noted by Briones (2020), successful AI implementation relies not only on the inseminator's technique but also on proper breeding documentation and timely synchronization of insemination with the animal's reproductive cycle. Inadequate farm data make it challenging to predict estrus accurately, resulting in mistimed inseminations and lower conception rates. Interestingly, low-quality semen, improper handling ($\bar{x}$ = 2.39), AI technique errors, or inadequate training ($\bar{x}$ = 2.10) are among the least reported challenges. This signifies a generally high level of technical preparedness among inseminators in Negros Oriental. The minimal concern over handling procedures reflects the success of government-sponsored training, quality assurance mechanisms, and semen source control. Correspondingly, Ybañez et al. (2017) concluded that consistent skills development and access to certified semen sources significantly improve inseminator performance and overall AI outcomes.

These results imply that the key drivers of AI success lie outside the inseminators' control, mainly within animal care practices and environmental factors. Therefore, interventions should expand beyond technician training to enhance conception rates and improve UNAIP delivery. There is a pressing need to integrate farmer education modules focusing on nutritional management, climate-related stress mitigation, and systematic reproductive monitoring. Equipping farmers with these skills can ensure that the groundwork for successful AI is in place before technicians are called to deliver services. Although not directly included in the original Statement of the Problem, additional insights were gathered to enrich the study by exploring the perceived success rate of AI and the incentive structures tied to inseminator performance. These data offer valuable context in understanding the effectiveness and sustainability of UNAIP implementation from the perspective of service providers. The following figures present these supplementary findings.

Figure 1 illustrates the perceived Success rate of AI in terms of positive conception outcomes, as reported by the inseminators. Notably, 50% of the respondents considered the conception success rate high, while 10% rated it as very high, suggesting that a significant majority view AI as an effective reproductive strategy. This reflects positively on the technical capability of inseminators and the effectiveness of the AI delivery process under the current implementation of UNAIP in Negros Oriental. Conversely, only 6% of respondents perceived the success rate as low, indicating that poor outcomes were relatively rare. These findings support the observations of Ybañez et al. (2017), who noted that a well-trained AI workforce and consistent field practices contribute to improved conception rates, especially when proper timing, cow health, and semen quality are maintained. However, the variability in perception may also be influenced by environmental factors, cow condition, and farmer cooperation—challenges noted in the earlier tables. According to Soriano et al. (2021), even well-executed AI procedures may fail if cows are nutritionally stressed or heat detection is inaccurate. The majority perception of AI as effective implies strong baseline competence among technicians, but continued efforts in farmer education and environmental management remain essential for optimizing outcomes.

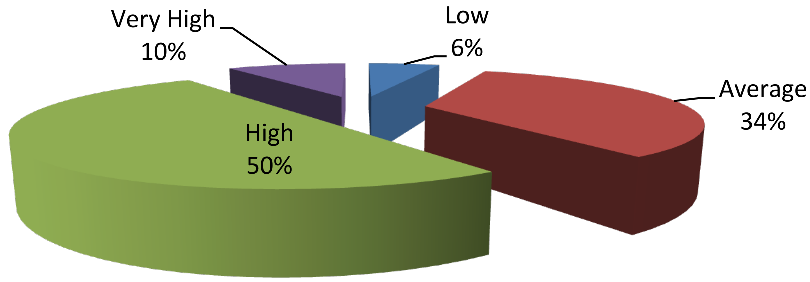

Figure 1. *Perceived Success Rate of AI in terms of Conception*

Figure 2 presents the distribution of incentives or rewards artificial inseminators receive upon achieving successful inseminations. A substantial majority (77%) of the respondents reported receiving monetary incentives, highlighting the importance of financial motivation in sustaining technician engagement and performance. A smaller proportion (8%) indicated receiving non-monetary incentives, such as recognition, certificates, or material support. At the same time, a notable number of inseminators shared that they did not receive any form of incentive, either monetary or non-monetary. These findings emphasize the role of incentive structures in motivating AI service providers. Briones (2020) states that providing performance-based rewards, especially monetary compensation, enhances technician accountability, increases AI coverage, and promotes program retention. This is especially relevant in rural areas, where inseminators often face rugged terrain, logistical challenges, and limited institutional support. The low percentage of non-monetary incentives suggests that recognition mechanisms may not be consistently institutionalized across LGUs, despite their potential to reinforce intrinsic motivation and professional identity, as Peralta observes (2024).

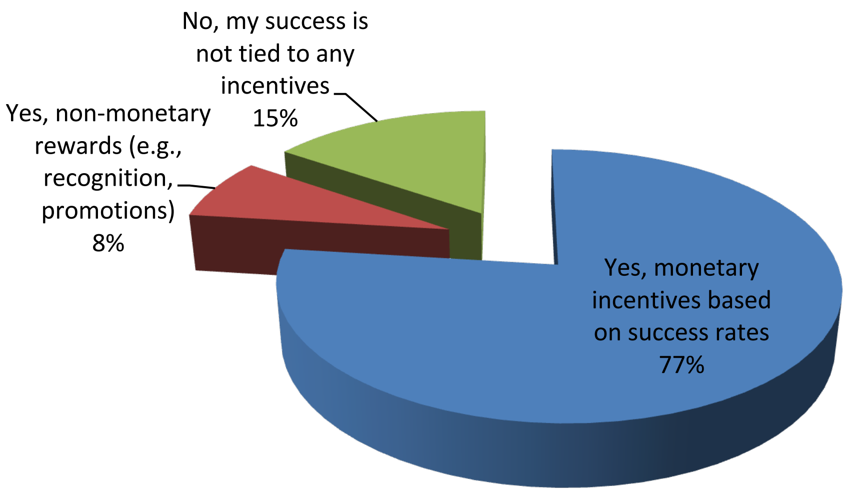

Figure 2. *Incentives or Rewards tied to Success as an Artificial Inseminator (n=52)*

The presence of inseminators who report receiving no incentives at all also raises concerns about disparities in program implementation. It implies that some LGUs or agencies may lack the budgetary provisions or administrative systems to deliver appropriate rewards, potentially affecting technician morale and long-term commitment. As recommended by the Department of Agriculture (2023) under the UNAIP framework, harmonizing incentive systems and ensuring consistent implementation across regions are key strategies to enhance the delivery and quality of AI services.

3.9 Relationship between the Extent of Support Received by the Artificial Inseminators and the Extent of Challenges Experienced

Table 9 presents the relationship between the extent of support received by artificial inseminators and the challenges they experienced in implementing AI services under the UNAIP. Using Spearman's Rank-Order Correlation at a 0.05 level of significance, the results reveal statistically significant relationships between specific support types and service delivery challenges. In particular, support for professional development demonstrated a moderate positive correlation with low service delivery quality (r = 0.490, p = 0.000), while support for equipment and storage facilities also showed a moderate positive correlation with the same challenge indicator (r = 0.310, p = 0.024). However, no significant relationships were found between both types of support and the success rate of insemination procedures (r = 0.210, p = .131 and r = 0.200, *p* = .160, respectively).

Table 9. *Relationship between the Extent of Support Received by the Artificial Inseminators and the Extent of Challenges Experienced*

Bivariate Factors	r_s	p	Decision	Remark
Support on Professional Development vs Low Quality of Service Delivery	0.49	0.000	Reject H_o	Significant
Support on Equipment and Storage Facilities vs Low Quality of Service Delivery	0.31	0.024	Reject H_o	Significant
Support on Equipment and Storage Facilities vs Success Rate	0.21	0.131	Fail to reject H_o	Not significant
Support for Professional Development vs Success Rate	0.20	0.160	Fail to reject H_o	Not significant

Note: Between ± 0.50 to ± 1.00 (strong); ± 0.30 to ± 0.49 (moderate); ± 0.10 to ± 0.29 (weak); ± 0.01 to ± 0.09 (very weak)

At first glance, the positive correlations between support and service delivery challenges may seem counterintuitive, since support is typically expected to reduce, not correlate with, increased challenges. However, these findings likely reflect a reactive support pattern, where interventions are provided after problems have already been identified, rather than serving as preventive measures. This is consistent with Peralta's (2024) observation that support services are often concentrated in areas already experiencing service delivery breakdowns, particularly in GIDAs. Edale (2025) similarly reported that support, such as training or equipment distribution, tends to be mobilized in response to declining performance, rather than implemented proactively across all service areas. This reactive pattern points to a strategic mismatch between support delivery and actual field needs. Instead of preventing challenges, current practices may reinforce a cycle where support only reaches inseminators once difficulties have escalated. This highlights the need for anticipatory and sustained support mechanisms that address potential bottlenecks before they impact service quality. Chandran et al. (2025) argued that institutional responses risk failing to address systemic service delivery gaps without strategic foresight and continuous capacity building.

Furthermore, the absence of significant correlations between support and AI success rates suggests that equipment and training alone are insufficient to ensure positive reproductive outcomes. This reinforces the findings of Soriano et al. (2021) and Valdez (2024), who stressed that factors beyond technician capacity, such as cow health, nutrition, reproductive management, and farmer cooperation, play greater roles in determining AI success. Even highly trained inseminators with adequate tools cannot compensate for poor on-farm conditions, such as nutritionally stressed animals or improper heat detection by farmers. Tadesse et al. (2022) and Peña and Lañada (2019) similarly emphasized that successful AI outcomes depend on synchronized efforts between inseminators and farmers, supported by a conducive farm environment. These results have important practical and policy implications. Program managers should shift from a reactive to a proactive support model, ensuring that training, equipment, and logistical resources are distributed equitably and consistently, not just in areas reporting problems. This requires routine monitoring and early identification of at-risk service areas, followed by preventive capacity-building interventions.

Moreover, policies should promote a holistic support framework beyond technician training and equipment provision. This includes farmer-focused education on reproductive management, improved cold chain logistics, and synchronized investments in technician capacity, infrastructure, and farmer engagement, as Briones (2020) emphasized. Supporting both the supply side (inseminators) and the demand side (farmers) is essential for closing the gap between service delivery and reproductive outcomes. In summary, while artificial inseminators receive some support, the findings highlight that when and how support is delivered is just as important as what is delivered. Moving toward a sustained, anticipatory, and farmer-inclusive support model will help prevent service breakdowns, enhance AI success rates, and strengthen the overall impact of UNAIP in Negros Oriental and similar rural settings.

4.0 Conclusion

The implementation of the UNAIP for cattle in Negros Oriental highlights the growing potential of artificial insemination (AI) as a transformative strategy for livestock development. However, its long-term success relies not only on awareness and technical capacity but also on a responsive, integrated support system that reflects the socio-environmental realities of rural cattle production. While farmers demonstrated high levels of awareness regarding AI benefits and procedures, knowledge alone does not guarantee adoption or success. Effective implementation requires culturally sensitive extension mechanisms that empower farmers and inseminators to navigate environmental, logistical, and institutional barriers.

A key contribution of this study is the finding that cultural beliefs—often viewed as impediments—can serve as enablers of procedural awareness when aligned with community-centered training. This insight challenges dominant narratives in agricultural innovation literature and adds a new perspective to culturally embedded technology adoption discourse. Additionally, the positive correlation between institutional support and service challenges reveals a pattern of reactive support provision, highlighting the need for anticipatory program design. The weak association between support systems and AI success rates reinforces the argument that technical inputs must be matched by cow health, heat detection accuracy, and farmer engagement, validating both Systems Theory and the Diffusion of Innovations framework.

The study has practical implications for policymakers and implementers. It underscores the importance of shifting UNAIP from a purely technical program into a community-driven, inclusive, and farmer-informed initiative, grounded in scientific and socio-cultural realities. Specific actions include harmonizing incentive systems, expanding farmer education on reproductive management, and improving support infrastructure in geographically isolated areas. This study's limitations include its geographic focus on a single province and reliance on self-reported perceptions, which may introduce response bias. These constraints suggest that the informative findings may not be fully generalizable across regions. Future research should expand to other provinces for comparative analysis, incorporate mixed methods or longitudinal tracking to assess behavioral change over time, and explore the economic viability and health management practices that influence AI success. In addition, the perspectives of other stakeholders, such as veterinarians, program funders, and cattle owners in low-performing areas, should be integrated to deepen understanding of the AI ecosystem in rural Philippines.

5.0 Contributions of Authors

The authors confirm their equal contribution to every part of this research. All authors reviewed and approved the final version of this paper.

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7.0 Conflict of Interests

This study has no conflict of interest of any sort.

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