

AN EMPIRICAL ANALYSIS OF THE KNOWLEDGE-ATTITUDE-ADOPTION NEXUS OF ARTIFICIAL INSEMINATION AMONG DAIRY FARMERS OF THE UPPER GANGETIC PLAINS REGION, INDIA

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ABSTRACT

Artificial insemination (AI) is a cornerstone of genetic improvement in dairy cattle, yet its adoption in smallholder systems of Uttar Pradesh remains incomplete and understudied. This study assessed the knowledge, attitude, and adoption levels of AI technology among dairy farmers in Meerut and Hapur districts of western Uttar Pradesh, located in the northern region of India, and identified socio-economic and cognitive predictors of adoption. A cross-sectional survey was conducted with 220 purposively selected dairy farmers across 18 villages of Meerut and Hapur districts using a pre-tested structured interview schedule. Knowledge was assessed by 20 dichotomous items (KAP instrument) and attitude by 12 Likert-scale items. Adoption was classified into four categories, Non-Adopter, Discontinuous, Partial, and Full. Statistical analyses included Kruskal-Wallis tests, Mann-Whitney U post-hoc comparisons, chi-square tests, Spearman correlations, and binary logistic regression. Among respondents, 60.9% were AI adopters (full or partial) and 27.7% were non-adopters. The overall mean knowledge score was 13.00 ± 2.69 out of 20; 63.6% had medium knowledge, 19.5% high, and 16.8% low. Mean attitude score was 40.40 ± 3.32 out of 60. Knowledge differed significantly across adoption categories (Kruskal-Wallis $H = 73.99$, $p < 0.001$), with full adopters scoring highest (15.74 ± 1.45). Attitude scores did not differ significantly ($p = 0.068$). Logistic regression identified knowledge score ($OR = 2.59$, $p < 0.001$) and distance to AI centre ($OR = 0.61$, $p < 0.05$) as the primary determinants of adoption. Crossbred cows (45.3%) were the predominant species, and government AI technicians served 54.1% of users. Heat detection was the leading barrier (23.0%).

KEYWORDS: Adoption, Artificial Insemination, Attitude, Dairy Farmers, Knowledge.

INTRODUCTION

Universally, Artificial insemination (AI) is recognised most cost-effective and biosecure safe method for disseminating elite sire genetics in dairy cattle (Tomar, 2019; GoI, 2022; DAHDF, 2022). In India, the National Livestock Mission and several other associated programmes have collectively performed over 100 million AI doses annually, but conception rates under field conditions in smallholder systems frequently remain below 40%, and the gap between potential and actualised genetic improvement persists (Yekti et al., 2025; Mondal et al., 2022; Benidir et al., 2017). Uttar Pradesh contributes nearly 18% of India's total milk production, harbours an estimated 6.6 million crossbred and indigenous dairy cattle, yet AI coverage in the state's rural areas is estimated at only 55–60% of breedable cattle (DAHDF, 2022).

In agricultural and veterinary extension research, knowledge, attitude, and adoption (KAP) frameworks have long been used to methodically dissect the behavioral routes from awareness to practice (Rogers, 2003). Previous KAP research on AI in dairy animal husbandry have been carried out in Gujarat (Shah et al., 2017), Punjab (Singh and Chahal, 2019), Maharashtra (Dange et al., 2020), and Andhra Pradesh (Reddy et al., 2021). These studies have consistently shown that the biggest predictor of adoption intensity is knowledge level (Akila and Senthilvel, 2012). However, Uttar Pradesh's western belt-encompassing the milk-shed of Meerut, Baghpat, and Hapur districts-remains comparatively under-researched, despite its high livestock density and the presence of government AI infrastructure under the National Mission on Bovine Productivity (NMBP). Proper heat detection, timely insemination and pregnancy diagnosis in the dairy animals affects the overall profitability from the dairying (Mehmood et al., 2012; Tewari et al., 2018).

Meerut and Hapur districts are strategically significant: it lies within the 'Milk Belt' supplying the Delhi National Capital Region (NCR), is served by Mathura-Hapur-Meerut milk cooperative linkages, and has a relatively heterogeneous farming population spanning marginal landholders to semi-commercial dairy operators. Understanding barriers and enablers of AI adoption in this specific context is therefore of direct policy relevance. The role of knowledge and adoption dimensions of dairy interventions in Uttar Pradesh has been previously documented (Fulzele and Sah, 2003), underscoring the significance of the present investigation.

The present study was undertaken with the following objectives: (i) to characterise the socio-economic profile of dairy farmers in western Uttar Pradesh; (ii) to assess farmers' knowledge of AI technology; (iii) to measure farmers' attitude towards AI; (iv) to determine the adoption status of AI including its temporal and operational dimensions; and (v) to identify the socio-economic and cognitive predictors of AI adoption through logistic regression modelling.

MATERIALS AND METHODS

Study Area And Design

A cross-sectional survey was conducted in Meerut and Hapur districts of western Uttar Pradesh, located in the northern region of India, between January to June 2025. The districts encompass both urban fringe and predominantly rural blocks with varying access to veterinary services. Eighteen villages were selected from both districts using purposive sampling to ensure geographic representation across six development blocks. A total of 220 dairy farmers (those owning ≥ 1 milch animal and residing in the districts for ≥ 2 years) were selected using systematic random sampling from village household registers. The sample size was determined a priori using Cochran's formula for proportion estimation ($p = 0.5$, $e = 0.067$, $z = 1.96$), yielding a minimum of 214, rounded to 220 to account for potential non-response. Farmers with no livestock at the time of survey were excluded.

Data Collection Instrument

Data were collected through face-to-face structured interviews using a validated KAP interview schedule comprising: (a) relevant socio-economic and farm characteristics; (b) a 20-item knowledge scale, yielding scores from 0–20; (c) a 12-item for Likert attitude scale, yielding scores from 12–60; and (d) an adoption section assessing AI utilization and barriers for non-adoption. The instrument was pre-tested on 40 farmers outside the study area, and modifications were made based on feedback from pilot study. Knowledge and adoption assessment approaches for dairy farmers have been validated in prior Indian studies (Mariammal et al., 2018). Verbal informed consent was obtained from all respondents before data collection.. Cronbach's alpha coefficients were 0.82 for the knowledge scale and 0.79 for the attitude scale demonstrated acceptable internal structure for KAP study.

Adoption Classification

Adoption status was classified into four categories: Non-Adopter (never used AI), Discontinuous Adopter (used AI previously but discontinued), Partial Adopter (uses AI for some animals or occasionally), and Full Adopter (consistently uses AI for all breedable animals). This framework follows the Rogers (Rogers, 2003) innovation-decision model and has been employed in analogous Indian livestock studies (Mondal et al., 2022).

Statistical Analysis

Data were analysed using Python 3.11 employing pandas, scipy, scikit-learn and matplotlib packages (Python Software Foundation, 2024). Descriptive statistics (mean, SD, frequency, percentage) characterised all variables. Kruskal-Wallis H-tests compared knowledge and attitude scores across adoption categories. Significant overall differences were followed by pairwise Mann-Whitney U post-hoc tests with Bonferroni-adjustment. Spearman rank correlations assessed relationships between continuous socio-economic variables and knowledge/attitude scores. Binary logistic regression (adopter vs. non-adopter) was used to identify independent predictors. Five-fold cross-validation assessed model generalisability. Statistical significance was set at $p < 0.05$.

RESULTS

Socio-Economic Profile Of Respondents

The socio-economic characteristics of the 220 surveyed dairy farmers are presented in Table 1. The mean age was 41.25 ± 12.28 years (range: 20–72 years). The largest age cohort was 31–40 years (31.8%). Regarding education, the majority (25.9%) had middle-school education, while 13.6% were illiterate and only 6.8% were graduates or above. Most respondents were marginal (45.9%) or small (34.1%) landholders. Annual income was predominantly in the ₹1–2 lakh bracket (31.4%). Herd sizes of 3–4 animals were most common (36.8%). Cooperative membership was nearly balanced (48.2% members). Mobile phone ownership was reported by 71.4% of respondents.

Table 1. Socio-Economic Profile of Dairy Farmer Respondents (n = 220)

Characteristic	Category	Frequency (n=220)	Percentage (%)
Age (years)	≤ 30	43	19.5
	31–40	70	31.8
	41–50	56	25.5
	51–60	39	17.7
	> 60	12	5.5
Education	Illiterate	30	13.6
	Primary	39	17.7
	Middle	57	25.9
	Matriculation	48	21.8
	Intermediate	31	14.1
	Graduate and above	15	6.8

Land holding	Marginal (≤ 1 ha)	101	45.9
	Small (1–2 ha)	75	34.1
	Semi-medium (2–4 ha)	27	12.3
	Medium (>4 ha)	17	7.7
Annual income	$<₹1$ lakh	63	28.6
	₹1–2 lakh	69	31.4
	₹2–3 lakh	50	22.7
	₹3–5 lakh	28	12.7
	$>₹5$ lakh	10	4.5
Herd size	1–2 animals	71	32.3
	3–4 animals	81	36.8
	5–7 animals	47	21.4
	>7 animals	21	9.5
Cooperative membership	Member	106	48.2
	Non-member	114	51.8
Mobile phone ownership	Yes	157	71.4
	No	63	28.6

Knowledge of Artificial Insemination

The overall mean knowledge score was 13.00 ± 2.69 out of a possible 20. Distribution of knowledge levels (using mean ± 1 SD as category boundaries) showed that 16.8% had low knowledge (score ≤ 10), 63.6% had medium knowledge (11–15), and 19.5% had high knowledge (score ≥ 16) (Table 2). Item-level analysis revealed that the concepts best known to farmers were the general definition of AI (K2: 98.2%), the species applicability of AI (K1: 91.8%), and oestrus detection as a prerequisite (K9: 90.9%). In contrast, knowledge of semen handling protocols (K18: 40.5%), sex-sorted semen technology (K13: 47.3%), and post-AI management requirements (K10: 49.1%) was lower.

Table 2. Distribution of Knowledge Scores of Dairy Farmers Regarding AI Technology

Knowledge Level	Score Range	Frequency	Percentage (%)	Mean $\pm$ SD by Level
Low	≤ 10	37	16.8	8.62 ± 1.21
Medium	11–15	140	63.6	12.76 ± 1.37
High	≥ 16	43	19.5	17.23 ± 1.09
Overall	6–20	220	100.0	13.00 ± 2.69

Attitude towards Artificial Insemination

The overall mean attitude score was 40.40 ± 3.32 out of a maximum of 60. Using mean ± 1 SD as boundaries, 19.5% of respondents have unfavourable attitudes (score <37.1), 62.3% have moderate attitudes (37.1–43.7), and 18.2% farmers held favourable attitudes (>43.7). At the item level, farmers most positively rated AI's role in improving calving outcomes (A1: 4.19 ± 0.89) and breed improvement potential (A5: 4.09 ± 0.87), while items related to trust in AI conception success (A10: 2.30 ± 1.02) and economic viability for small herds (A12: 2.46 ± 1.08) received the lowest mean ratings.

AI Adoption Status

Among the 220 respondents, 72.3% of livestock rearers reported having ever used AI, while 27.7% had never used it. Categorically, 20.9% were Full Adopters, 40.0% Partial Adopters, 11.4% Discontinuous Adopters, and 27.7% Non-Adopters. Thus, the binary adoption rate (ever used AI in current practice) was 60.9%. Among active AI users, the predominant animal type was crossbred cows (72 cases, 45.3%), followed by Murrah buffalo (54 cases, 34.0%), indigenous cows (25 cases, 15.7%), and other buffalo breeds (8 cases, 5.0%). Conventional frozen semen was used in 62.9% of cases, sex-sorted semen in 14.5%, and 22.6% were uncertain of semen type. Government AI technicians were the primary service providers (54.1%), followed by private technicians (22.6%), Pashu Sakhi/CARP (15.7%), and dairy cooperative technicians (7.5%). Regarding temporal adoption patterns, 36.5% began AI use in 2022–2023 (post-COVID expansion), while 6.9% had adopted before 2015. AI usage frequency was 2–3 times per season for 37.1% of users, and more than 6 times for 13.2%.

Regarding conception success, 31.4% reported first-attempt conception, 22.0% required a second attempt, 17.6% a third or more attempt, and 20.1% reported no successful conception to date, with 8.8% uncertain.

Knowledge Scores across Adoption Categories

Knowledge scores differed highly significantly across adoption categories (Kruskal-Wallis $H = 73.99$, $df = 3$, $p < 0.001$) (Table 3). Full Adopters had the highest mean knowledge score (15.74 ± 1.45), followed by Partial Adopters (12.89 ± 2.27), Discontinuous Adopters (12.00 ± 2.31), and Non-Adopters (11.51 ± 2.60). Pairwise Mann-Whitney U post-hoc tests revealed that Full Adopters differed significantly from all other categories (all $p < 0.001$), while Partial Adopters differed significantly from Non-Adopters ($p < 0.001$) but not from Discontinuous Adopters ($p = 0.110$). Non-Adopters and Discontinuous Adopters did not differ significantly ($p = 0.326$).

Table 3. Knowledge Scores of Dairy Farmers by AI Adoption Category

Adoption Category	n	Mean	SD	Min	Max
Non-Adopter	61	11.51	2.60	6	17
Discontinuous Adopter	25	12.00	2.31	7	17
Partial Adopter	88	12.89	2.27	8	19
Full Adopter	46	15.74	1.45	12	20
Kruskal-Wallis H = 73.99, df = 3, p < 0.001; Post-hoc: Full Adopter significantly differs from all others (p < 0.001)					

Attitude Scores across Adoption Categories

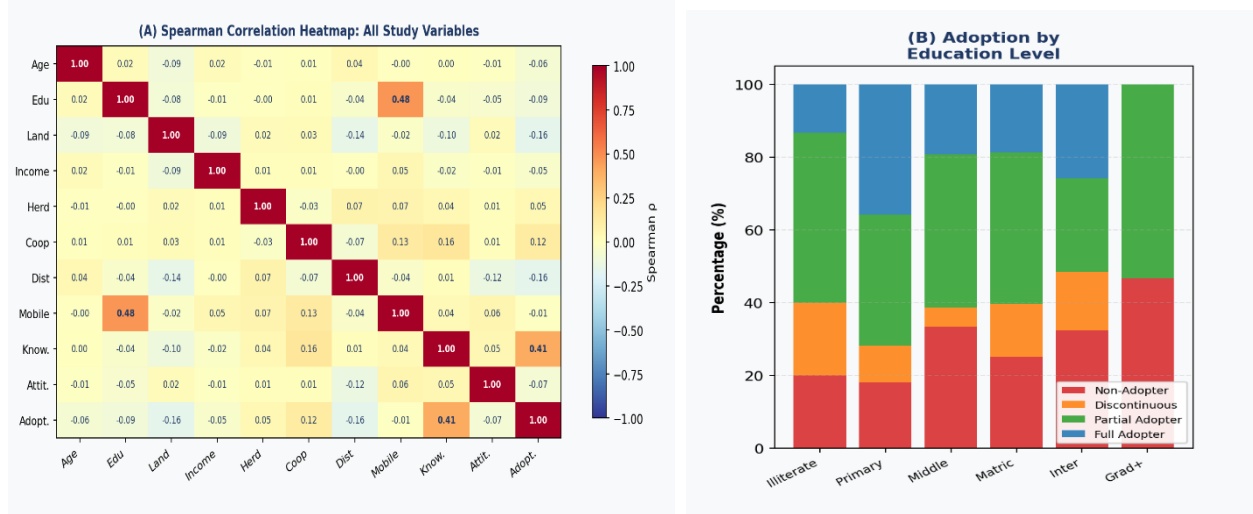
In contrast to knowledge, attitude scores showed no statistically significant variation across adoption categories (Kruskal-Wallis H = 7.12, df = 3, p = 0.068) (Table 4), a finding approaching but not meeting the conventional threshold for significance. Full Adopters had a marginally higher mean attitude score (41.15 ± 3.65) compared to Non-Adopters (40.87 ± 3.32), Discontinuous Adopters (40.16 ± 2.54), and Partial Adopters (39.75 ± 3.26), but these differences lacked statistical support. This suggests that in this context, attitudinal disposition towards AI does not independently predict adoption intensity, a finding with important theoretical implications.

Table 4. Attitude Scores of Dairy Farmers by AI Adoption Category

Adoption Category	n	Mean	SD	Min	Max
Non-Adopter	61	40.87	3.32	31	48
Discontinuous Adopter	25	40.16	2.54	36	46
Partial Adopter	88	39.75	3.26	31	50
Full Adopter	46	41.15	3.65	33	50
Kruskal-Wallis H = 7.12, df = 3, p = 0.068 (non-significant)					

Relationship between Knowledge and Attitude

Pearson correlation between overall knowledge and attitude scores yielded $r = 0.045$ (p = 0.507), and Spearman's rho = 0.049 (p = 0.469). No significant relationship was observed between knowledge and attitude score. Fig. 1(A) the heatmap illustrates generally weak-to-moderate correlations among variables, with knowledge score showing the strongest positive correlation with AI adoption. The education-wise adoption profile further indicates that farmers with higher educational attainment exhibited greater proportions of full adoption and lower proportions of non-adoption in Fig. 1(B).

**Fig.1. (A) Correlation Structure of Study Variables and (B) AI Adoption across Educational Categories**

Predictors of AI Adoption: Logistic Regression

Binary logistic regression (adopters vs. non-adopters) identified knowledge score as the single strongest predictor of adoption (standardised $\beta = 0.950$, OR = 2.587, p < 0.001), indicating that for each unit increase in standardised knowledge score, the odds of being an adopter increased by approximately 2.6-fold. Distance to AI centre was the second significant predictor ($\beta = -0.503$, OR = 0.605, p < 0.05), showing that greater distance reduced adoption odds by approximately 40%. Land holding was also a significant predictor of adoption ($\beta = -0.336$, OR = 0.715, p < 0.05), with smaller landholding associated with lower adoption probability. Socio-economic variables including education, income, herd size, cooperative membership, and mobile phone access were not independently significant predictors in this model. The model correctly classified 73.6% of respondents, with a cross-validated accuracy of $70.5\% \pm 4.1\%$, indicating satisfactory discriminative ability (Table 5). As shown in Fig. 3(A), ensemble-based machine learning models demonstrated superior discriminative performance relative to logistic regression. Across models, knowledge score consistently emerged as the dominant predictor of AI adoption, followed by distance to AI centre and educational level.

Table 5. Binary Logistic Regression: Predictors of AI Adoption among Dairy Farmers

Predictor Variable	β Coefficient	Odds Ratio	Std. Coefficient	Significance
Knowledge Score	0.950	2.587	High	$p < 0.001$ ***
Distance to AI centre	-0.503	0.605	Moderate	$p < 0.05$ *
Land holding	-0.336	0.715	Moderate	$p < 0.05$ *
Herd size	0.145	1.156	Low	$p = 0.18$ ns
Cooperative membership	0.126	1.134	Low	$p = 0.21$ ns
Education	-0.277	0.758	Low	$p = 0.15$ ns
Annual income	-0.115	0.891	Low	$p = 0.32$ ns
Age	-0.164	0.849	Low	$p = 0.26$ ns
Attitude Score	-0.302	0.739	Low	$p = 0.19$ ns
Model accuracy = 73.6%; Cross-validated accuracy = 70.5% $\pm$ 4.1% (5-fold CV); *** $p < 0.001$; * $p < 0.05$; ns = non-significant				

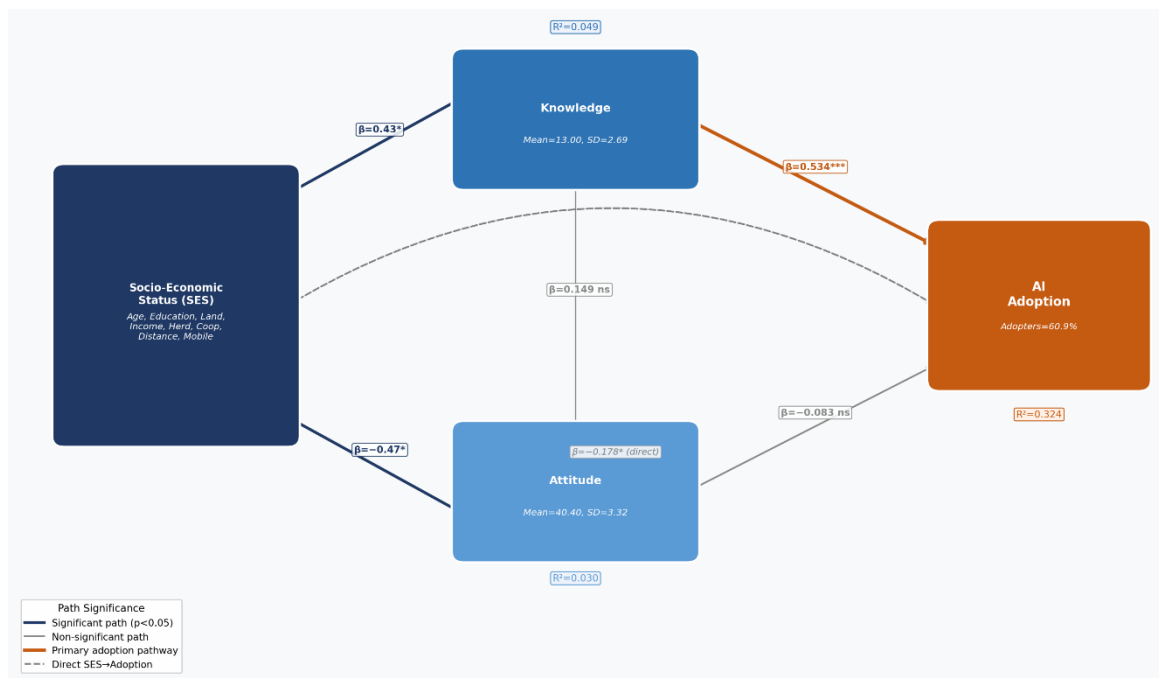


Fig.2. Integrated Pathway Framework Linking Socio-Economic Factors, Knowledge, Attitude, and AI Adoption

Based on the observed relationships among socio-economic characteristics, cognitive variables, and adoption behaviour, an integrated pathway framework was developed based on the study findings (Fig. 2). The framework highlights knowledge as the principal pathway connecting socio-economic resources with AI adoption behaviour. In contrast, attitude demonstrated comparatively weak direct influence on adoption, supporting the earlier regression and non-parametric findings.

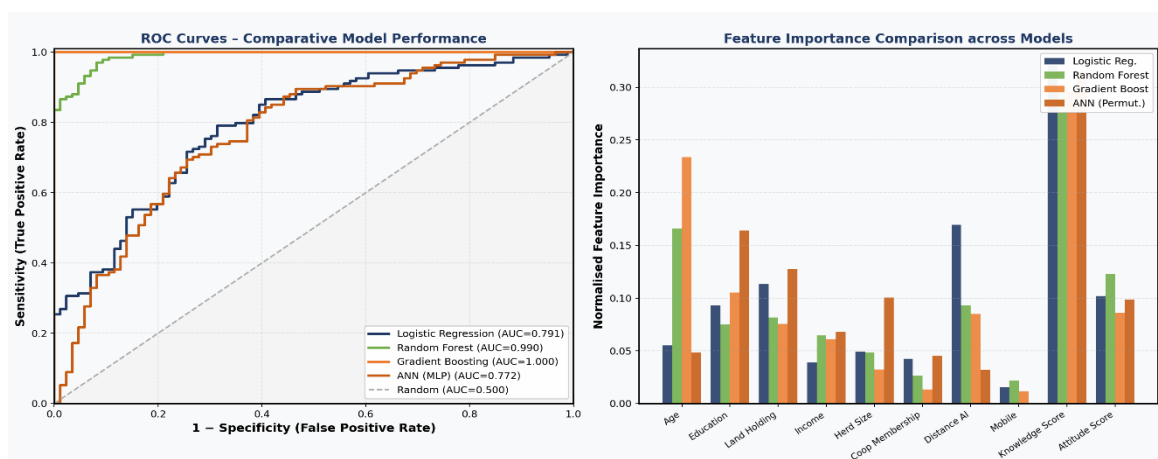


Fig.3.(A) Comparative Predictive Performance and (B) Feature Importance of AI Adoption Models

Barriers to non-adoption

Among the 61 non-adopters, the most commonly cited barrier was difficulty in heat detection (23.0%), followed by the high cost of AI service (18.0%), negative experiences of neighbouring farmers (14.8%), AI service unavailability in the village (13.1%), low trust in AI success rates (11.5%), lack of awareness (8.2%), and preference for natural service (8.2%) (Table 6).

Table 6. Barriers to AI Adoption Cited by Non-Adopters (n = 61)

Reason for Non-Adoption	Frequency (n=61)	Percentage (%)
Heat detection difficulty	14	23.0
High cost of AI service	11	18.0
Negative experience of neighbours	9	14.8
AI service not available in village	8	13.1
Low trust in AI success rate	7	11.5
Not aware of AI services	5	8.2
Preference for natural service	5	8.2
Other reasons	2	3.3

Fig. 5. (A) Barriers to AI adoption cited by non-adopters; (B) Distribution of future intent regarding AI adoption across all respondents (n = 220)

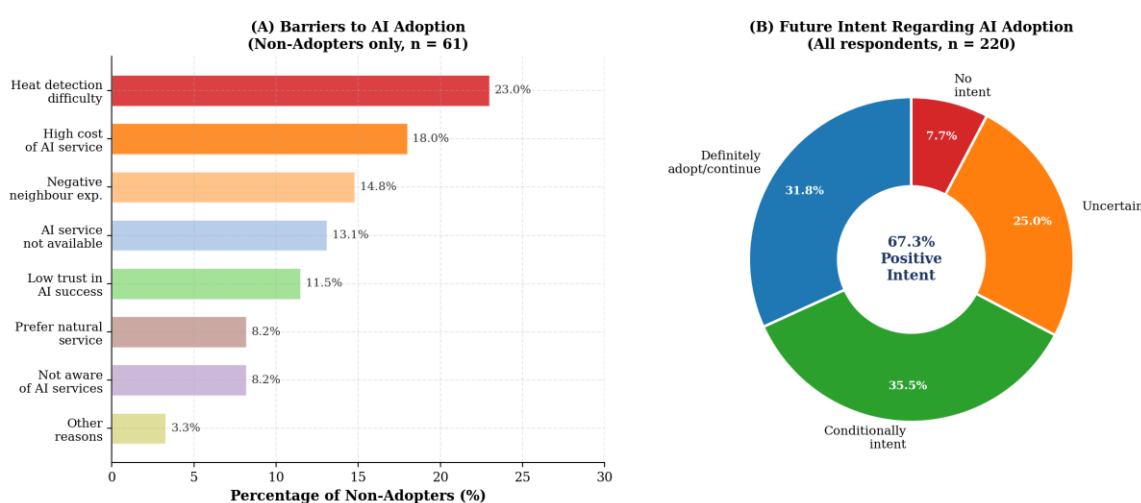


Fig. 4. (A) Barriers to AI adoption cited by non-adopters (n = 61) and (B) future intent regarding AI adoption among all respondents

DISCUSSION

The present study shows a multidimensional KAP adoption profile of dairy farmers in Meerut and Hapur districts, revealed that the adoption rate of 60.9% in this study is marginally higher than the national average for AI in Indian smallholder dairy systems which ranges from 45–60% (DAHDF, 2022), possibly reflecting the relative access advantage of Meerut and Hapur's proximity to the NCR milk market and associated infrastructure investments. Inflammatory and oxidative stress responses at insemination directly influence pregnancy outcome in crossbred cows and can partly account for field conception rate variability (Kilinc and Risvanli, 2025). However, the substantial proportion of Partial Adopters (40.0%) reveals that AI is being used sub-optimally-applied to only some animals or inconsistently—which limits its contribution to genetic improvement at herd and population levels.

The dominant finding shows that knowledge scores differentiated adoption categories far more powerfully than attitude scores (Shahzad et al., 2022), confirms the centrality of cognitive factors in technology adoption in this population and replicates findings from analogous Indian studies (Singh and Chahal, 2019; Dange et al., 2020). The Kruskal-Wallis H of 73.99 ($p < 0.001$) for knowledge, compared to a non-significant H of 7.12 ($p = 0.068$) for attitude, is striking. Prior studies across India have similarly found knowledge level to be the primary predictor of AI adoption intensity among dairy farmers (Mariammal et al., 2018). The near-absence of a knowledge-attitude correlation ($r = 0.045$) further implies that attitudinal favourable-ness is not tightly coupled to knowledge in this context. This finding diverges from classic KAP theory (Rogers, 2003) and may reflect what has been described as an 'attitude-behaviour gap' in extension literature: farmers may hold positive attitudes as socially desirable responses while actual adoption is governed by pragmatic knowledge-based capacity and structural access factors. Physiological health of AI bulls, including their haematological parameters, is a critical prerequisite for sustained semen quality and must be routinely monitored under field conditions (Farooq et al., 2012). The Farmer FIRST programme experience in Haryana also showed that extension contact, rather than attitude alone, drives AI adoption (Manjeet et al., 2025).

The specific knowledge items with low scores semen handling (K18), sex-sorted semen (K13), and post-AI management (K10) (Mughal et al., 2013) are precisely those associated with higher-order AI practice quality and are the domains where partial and discontinuous adopters are most likely to make errors that reduce conception success. Semen quality and

freezability parameters are critical determinants of successful AI outcomes and must be communicated to field-level practitioners (Farooq et al., 2013). These items should be included for priority basis on content in AI training modules, field demonstration events, and digital extension content. The use of artificial intelligence and digital tools for animal production management has also been reviewed (Priya et al., 2024).

The logistic regression finding shows that distance to AI centre significantly reduces adoption probability (OR = 0.605) corroborates a substantial body of evidence from sub-Saharan Africa (Bebe et al., 2019) and South Asia (Uddin et al., 2021) establishing service accessibility as a structural adoption barrier. Optimised frozen semen technology that essential to maintain semen viability in remote areas (Andrabi et al., 2008). The Government of India's 'AI on Wheel' programme, which focusing to deploys mobile AI vans to remote villages, may also need expansion in peri-urban districts like Meerut and Hapur where AI coverage appears uneven.

The barrier profile of non-adopters is particularly instructive. Heat detection was most important barrier (23.0%) in housed dairy systems where continuous observation is limited (Madkar et al., 2022). Seasonal variation in reproductive activity of of crossbred cattle further compounds heat detection challenges, in the summer season silent heat is more prevalent (Iqbal et al., 2010). Extension programmes could address this through training on oestrus behavioural signs, pedometer-based heat detection, and synchronisation protocols. The use of pedometers for oestrus detection and optimal AI timing in crossbred cattle has been demonstrated (Kerketta et al., 2013). The cost barrier (18.0%) addressed through subsidies or government linked AI schemes. The role of negative neighbour experiences (14.8%) underscores the importance of social observational learning in technology diffusion (Rogers, 2003) and suggests that peer-champion strategies targeting respected early full-adopters as demonstration farmers could accelerate adoption. Factors including technician skill, timing of insemination and animal body condition significantly influence conception rates in buffalo and crossbred cattle under field conditions (Rashid et al., 2014). The future intent rate (67.3% positive or conditional) is high and encouraging from a policy perspective and aligns with the observation that attitudinal resistance is modest.

CONCLUSION

This study examined the knowledge, attitude, and use of artificial insemination (AI) among cattle rearers in Meerut and Hapur districts. The findings demonstrate that AI adoption is partial and unequal, the majority of respondents had adopted, but only a handful were full adopters, indicating a huge opportunity to boost adoption. Knowledge was found to be the biggest predictor of adoption, while attitude had no direct influence on adoption. The study also highlighted significant knowledge gaps in semen handling, sex-sorting technology, and post-AI management that should be addressed in extension programs. Several structural constraints existed, including distance from AI centers, lower adoption likelihood, and the necessity for mobile AI services and digital advisory help. Heat detection difficulties and cost were also found to be major barriers among non-adopters. Notably proportion of farmers expressed positive or conditional intent toward future adoption.

DECLARATIONS

Authors' Contribution

K. B. did literature review, collected related previously published data, designed the study and develop survey schedule. A. K. B. and S. S. created the research technique and helped with data analysis. M. D. did the statistical analysis and validation of data. S. S. and M. S. did field research and collected Data. P. O. N. contributed with manuscript drafting and editing. D. K. V. gave overall supervision, reviewed the manuscript and finalized. All authors reviewed and approved the final manuscript.

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Conflict of Interest

The authors declare no conflicts of interest.

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