Human–AI Collaboration in Agriculture 2035: Designing A Farmer-Centred Intelligent Farming Ecosystem

Author

1. **Mr. Kudipudi Jnanendra Siva Kumar,** Research Scholar, BBA Department, KLEF, Vaddeswaram, jnanendrasvakumarkudipudi@gmail.com,

2 .Dr. Ajay Kumar Varshney, Professor, BBA Department, KLEF, Vaddeswaram.,

ABSTRACT

Agriculture is entering a technological transition in which artificial intelligence may become a regular component of farm-level decision-making. In 2035, farmers may interact with AI systems for crop monitoring, weather interpretation, pest identification, irrigation planning, resource management and market-related decisions. However, the future of agricultural intelligence should not be defined by automation alone. The more significant challenge is to determine how computational intelligence can work alongside human agricultural experience.

This study proposes a Farmer-Centred Human–AI Collaboration Framework for 2035 (FHACF-2035). The framework considers the farmer, rather than the technology, as the central decision-making participant. AI is positioned as an analytical partner capable of processing large and diverse datasets, while farmers contribute contextual knowledge, experience, values and practical judgment. The research focuses on six dimensions: perceived usefulness, trust, explainability, farmer autonomy, accessibility and climate-resilience value.

The study adopts a descriptive and exploratory research design supported by primary questionnaire data and secondary evidence. A proposed sample of 300 agricultural stakeholders is used for the empirical component, with farmers forming the major respondent group. A five-point Likert scale is proposed for measuring perceptions, while descriptive statistics, reliability analysis, correlation, regression and group-comparison techniques are proposed for data analysis.

Current evidence indicates that agricultural AI is already moving into practical deployment. India is using AI for farmer advisories, pest surveillance, crop identification, insurance and agricultural governance. The National Pest Surveillance System, for example, uses AI and machine learning and is being used by more than 10,000 extension workers. Internationally, FAO and the World Bank are emphasizing responsible, inclusive and context-specific agricultural AI rather than technology deployment alone.

The study argues that the agricultural AI of 2035 should follow a “recommend–explain–evaluate–decide–learn” cycle. Such a model can combine computational capability with farmer knowledge and create an agricultural ecosystem that is more transparent, accessible, resilient and human-centred.

Keywords: Artificial Intelligence, Human–AI Collaboration, Agriculture 2035, Smart Farming, Farmer-Centred AI, Agricultural Decision-Making, Responsible AI, Climate Resilience, Digital Agriculture.

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1. INTRODUCTION

Agriculture has always depended on decision-making under uncertainty. Farmers decide what to cultivate, when to sow, how much water and fertilizer to apply, how to respond to pests and when to harvest despite incomplete information about weather, markets and field conditions.

Artificial intelligence introduces a new type of agricultural capability. Instead of depending exclusively on historical experience or periodic expert advice, farmers can increasingly access systems capable of processing weather observations, satellite imagery, crop photographs, soil information, farm histories and other datasets.

The development is already visible in India. Government programmes are using AI and machine learning for areas including farmer advisories, pest management, crop identification, insurance and governance analytics.

At the same time, current agricultural AI initiatives indicate that accessibility matters as much as technological capability. The World Bank describes emerging Indian applications in which farmers receive localized information about crops, pests, weather and markets through basic smartphones and local-language interfaces.

This creates an important research question for 2035:

What should the relationship between a farmer and an intelligent agricultural system look like?

A future in which machines make all agricultural decisions may reduce the importance of human knowledge. A future in which technology is ignored may prevent farmers from benefiting from powerful analytical tools. Human–AI collaboration provides a third possibility: AI contributes computational intelligence while humans retain contextual judgment and decision authority.

This study therefore moves beyond the question of whether farmers will adopt AI. It investigates how farmers and AI can work together effectively.

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2. BACKGROUND OF THE STUDY

Agricultural AI is developing across several interconnected areas.

2.1 Crop Intelligence

AI can analyse crop images, satellite information and sensor observations to identify crop stress and potential disease.

2.2 Weather Intelligence

AI-supported forecasting can convert weather information into farm-level recommendations concerning sowing, irrigation and crop protection.

2.3 Pest Intelligence

Image-based systems can assist in identifying pests and recommending appropriate interventions.

2.4 Resource Intelligence

AI can potentially improve the timing and quantity of water, fertilizer, pesticides and other inputs.

2.5 Market Intelligence

Agricultural AI can process market and supply-chain information to provide information relevant to selling and distribution.

2.6 Knowledge Intelligence

Generative AI and conversational systems can make agricultural information accessible through natural-language and voice interactions.

FAO's recent work emphasizes that agricultural AI needs to be inclusive, trusted, context-specific and connected to real agricultural needs. Its Digital Agriculture and AI Innovation Roadmap specifically highlights accountability, equity, security and data stewardship.

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3. REVIEW OF LITERATURE

3.1 Artificial Intelligence as an Agricultural Decision-Support Technology

It is possible to apply artificial intelligence (AI) for agricultural prediction, classification, optimization and information processing. The World Bank mentions applications in crop/livestock systems, advisory services, markets, logistics, finance and weather/climate.

The implication is that agricultural AI is multifunctional and takes many forms depending on the agricultural application.

3.2 Farmer-Centred Artificial Intelligence

A technology that is sophisticated but inaccessible is a technology wasted.

Therefore, a focus on language, context and economics is required to make agricultural AI truly farmer-friendly. In other words, the emphasis should be on how to apply AI for supporting farmers' decision-making rather than what the technology can achieve.

3.3 AI and Local Agricultural Knowledge

Many of farmers' decisions are local decisions.

Farmers have local knowledge about:

- Their soils
- Weather
- Crops
- Pests
- Labour
- Water
- Markets
- Practices

Therefore, to make the most of agricultural AI, it may be best to combine machine evidence with local judgement.

3.4 AI Explainability

A recommendation to "irrigate the crop today" may contain more value if the recommendation includes an explanation. An example of an AI recommendation with an explanation is:

Irrigate within 24 hours.

Reason: The estimated soil water potential is below the threshold, and temperatures are expected to be above average for the next two days.

Such an explanation can allow farmers to interpret whether the recommendation corresponds to their local conditions.

3.5 AI, Inclusion and the Digital Divide

The use of AI in agriculture will be different for different farmers due to differences in:

- Access to smartphones
- Internet
- Education
- Digital literacy
- Income
- Language
- Extension

The World Bank highlights the importance of infrastructure, skills, governance and inclusion for agricultural AI in India.

3.6 AI and Climate Resilience

Climate variability increases the need for timely agricultural information.

AI can potentially analyse weather patterns, soil, crop and historical data to detect risks early and help take adaptive action. FAO's own strategic orientation towards agricultural AI fits within a context of climate resilience, sustainable agriculture and digital inclusion.

4. RESEARCH GAP

There is no doubt that the literature review demonstrates that there is a wealth of information on AI in agriculture. However, there is one key research gap. While most literature asks the question "What can AI do for agriculture?", this study asks the question "How can farmers and AI make agricultural decisions together?" The research gap lies in understanding the connections between human decision-making and machine decision-making. The following issues require further investigation:

1. What share of decision-making should be given to farmers?
2. How can farmers verify AI recommendations?
3. How can local knowledge be included in AI?
4. How can AI recommendations be explained?
5. How can agricultural data be governed?
6. How can AI serve small-scale resource-poor farmers?
7. How can Human-AI collaboration help climate-resilient agriculture?

This study attempts to contribute to the understanding of all of these issues by focusing on a farmer-centred approach.

5. STATEMENT OF THE PROBLEM

An AI recommendation can allow quicker decision-making than traditional agricultural advisory systems. However, the AI recommendation may not account for local conditions. For example, an AI irrigation recommendation may be based on weather forecasts and satellite data, while the farmer knows that a canal will be available the following morning. Similarly, an AI recommendation for disease control may be based on visual similarity, while the farmer knows that local conditions are different.

The study is concerned with the following problem: How can AI and farmers collaborate in 2035? Specifically, how can agricultural decision-making take advantage of both human and machine intelligence?

6. RESEARCH OBJECTIVES

Main Objective

To develop a farmer-centred framework for human-AI collaboration in agriculture by 2035.

Specific Objectives

1. To assess perceptions of AI-supported agricultural decision-making
2. To examine the relationship between perceived AI usefulness and adoption intention
3. To examine the role of trust in human-AI collaboration
4. To determine the importance of explainability for agricultural AI
5. To examine the importance of farmer decision autonomy
6. To study the role of accessibility and local language
7. To examine the perceived climate-resilience benefits of agricultural AI
8. To propose the FHACF-2035 framework

7. RESEARCH QUESTIONS

RQ1

What agricultural decisions do stakeholders think that AI can support by 2035?

RQ2

What factors influence stakeholders' willingness to adopt AI-based agricultural systems?

RQ3

Does explainability affect trust in agricultural AI?

RQ4

How important is farmer control in the context of conflicting human and machine decisions?

RQ5

Can the integration of farmer knowledge and AI affect perceived usefulness?

RQ6

What characteristics should an inclusive agricultural AI system possess by 2035?

8. HYPOTHESES

H1

Perceived AI usefulness is positively related to intention to adopt human-AI agricultural systems.

H2

Trust is positively related to adoption intention.

H3

Explainability is positively related to trust.

H4

Perceived farmer autonomy is positively related to acceptance of human-AI collaboration.

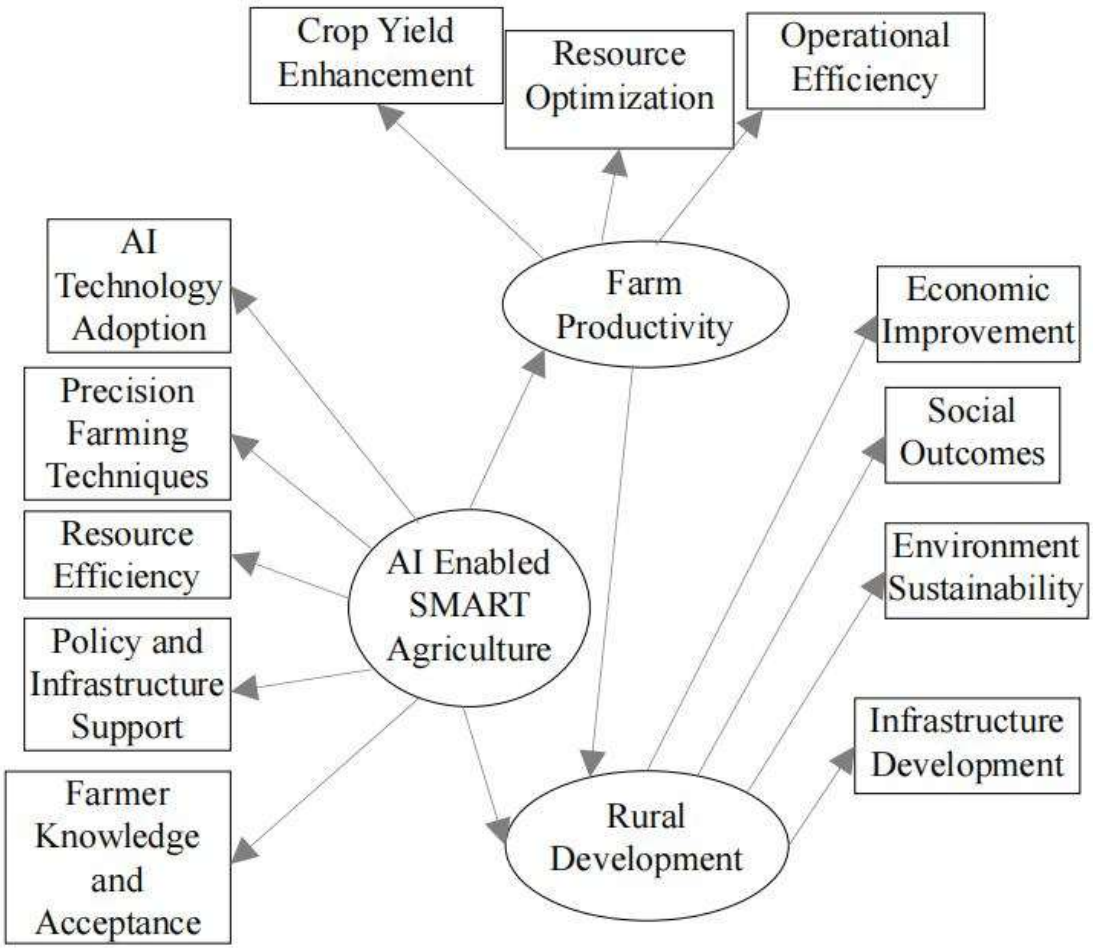
H5

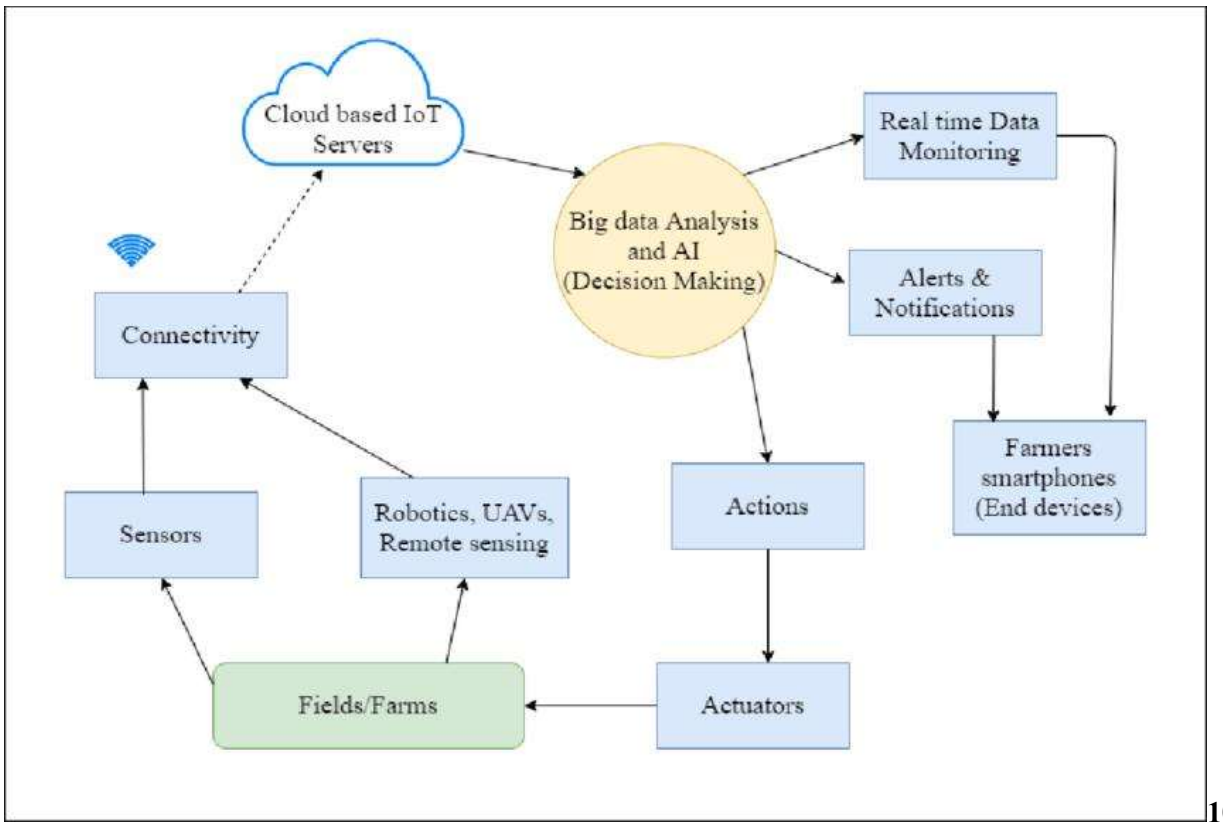
Accessibility is positively related to adoption intention.

H6

Perceived climate resilience is positively related to acceptance of agricultural AI.

9. CONCEPTUAL MODEL





10. RESEARCH METHODOLOGY

10.1 Research Design

This study proposes a descriptive , exploratory and future-oriented research design.

Descriptive

The descriptive component will focus on survey-based evidence on perceptions.

Exploratory

The exploratory component will seek to understand factors affecting agricultural AI collaboration.

Future-oriented

The future-oriented component will propose the FHACF-2035 framework.

10.2 Research Approach

This study proposes a mixed-method research approach.

Quantitative

The quantitative component will involve statistical analysis of survey data.

Qualitative

The qualitative component will involve conducting short interviews with experts/farmers.

11. RESEARCH POPULATION

The proposed research population consists of:

- Farmers
- Agricultural students
- Agricultural extension workers
- Agritech professionals
- Agricultural researchers
- Farmer Producer Organisation representatives

Farmers should constitute the majority of respondents.

12. RESEARCH SAMPLE

The proposed sample size is 300.
Category Proposed Sample Size
Farmers 220
Agricultural students 30
Extension personnel 20
Agritech professionals 15
Agricultural researchers/experts 15
Total 300
Important: These categories are proposed sample sizes, not actual survey results.

13. SAMPLING METHOD

A combination of purposive and stratified sampling can be used.
Farmers can be selected from different categories according to local growing conditions, while stratified sampling can be used to ensure representation across different respondent groups. If this study is limited to a single district/state, this should be specified in the final paper.

14. SOURCES OF DATA

Primary Data
Primary data will be collected using a questionnaire.
Secondary Data
Secondary data will be collected from government departments, ministry of agriculture and farmers welfare, ICAR, FAO, World Bank, NITI Aayog, journals, reports and digital agriculture programs.

15. QUESTIONNAIRE STRUCTURE

The questionnaire can be structured as follows:
SECTION A: RESPONDENT DEMOGRAPHICS (8 QUESTIONS)
1. Age
2. Gender
3. Education
4. Farming experience
5. Farm size
6. Type of farming
7. Location
8. Smartphone availability
9. Internet access

SECTION B: AWARENESS OF AI APPLICATIONS IN AGRICULTURE (4 QUESTIONS)
1. Have you heard about AI applications in agriculture?
2. Have you used any digital agricultural service?
3. Have you received any weather-based advisory service?
4. Have you accessed any mobile-based agricultural information service?

SECTION C: HUMAN-AI COLLABORATION IN AGRICULTURE (15 QUESTIONS + 5-POINT LIKERT SCALE)
Use a five-point scale from Strongly Disagree (1) to Strongly Agree (5)
STATEMENTS
1. AI can help farmers detect agricultural problems early
2. AI can help farmers arrive at better decisions
3. AI recommendations should include an explanation

4. Farmers should be able to reject AI recommendations
5. AI should be able to use farmers' local knowledge
6. Farmers should be responsible for major farm decisions
7. AI should provide information in regional languages
8. AI should function well under low connectivity
9. Farmers should know how their farm data is being used
10. AI can help farmers respond to climate risks
11. AI can help reduce wasteful use of agricultural inputs
12. AI can help farmers access agricultural expertise
13. AI should support farmers instead of replacing them
14. I would use an AI agricultural service if it is affordable
15. I would trust an AI recommendation more if it was verified by an agricultural expert
16. MEASUREMENT SCALE

Likert Scale: 1=Strongly Disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly Agree

MAJOR CONSTRUCTS

Construct Example Items
AI Usefulness Perceived practical value
AI Trust Confidence in recommendations
Explainability Ability to understand recommendations
Farmer Autonomy Ability to accept/reject decisions
Accessibility Cost-effectiveness and language
Climate Value Support for climate-related decisions
Adoption Intention Willingness to use AI

17. DATA COLLECTION PROCEDURE

The questionnaire can be distributed through direct farmer interaction, agricultural institutions, farmer groups, Google Forms, agricultural colleges and extension networks. Respondents should provide informed consent. After collection, the following procedure will be followed:

Responses → Screening → Coding → Data Entry → Statistical Analysis

18. DATA ANALYSIS

1. Data overview

Total submitted responses	61
Questionnaire items analysed	23
Data type	Categorical responses; ordinal response categories for usefulness and adoption intention
Descriptive analysis	Frequency and percentage
Inferential analysis	Chi-square tests of association; exploratory one-way ANOVA using ordinal scores

Important: These are 61 submitted responses, not the proposed sample of 300 mentioned elsewhere in the paper. The findings describe this sample and should not be generalized to all farmers.

2. Key results at a glance

Indicator	Leading response / grouping	n	% of valid answers
Adoption intention	Likely or Very likely	55	94.8%
Perceived usefulness	Useful or Very useful	42	73.7%
Digital access	Smartphone with regular internet	40	69.0%
Farmer decision authority	Farmer	24	42.1%
Trust signal	Verification by an agricultural expert	19	32.8%
Accessibility priority	Local/regional language	26	44.8%

Interpretation: 55 of 58 respondents (94.8%) said they were likely or very likely to use an AI service under the favourable conditions stated in the questionnaire. 42 of 57 respondents (73.7%) rated AI as useful or very useful for agricultural decisions.

3. Graphical representation of major findings

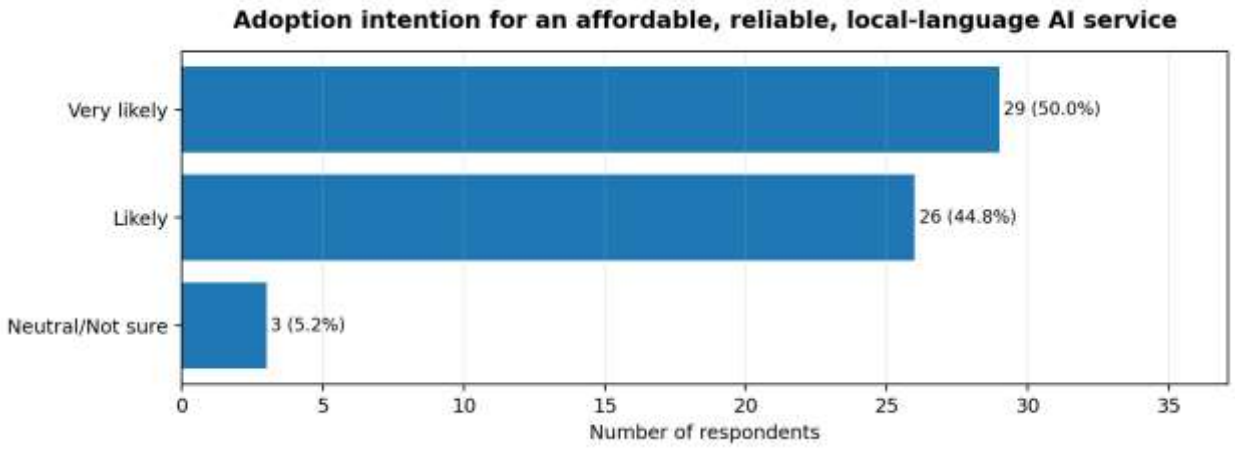


Figure 1. Adoption

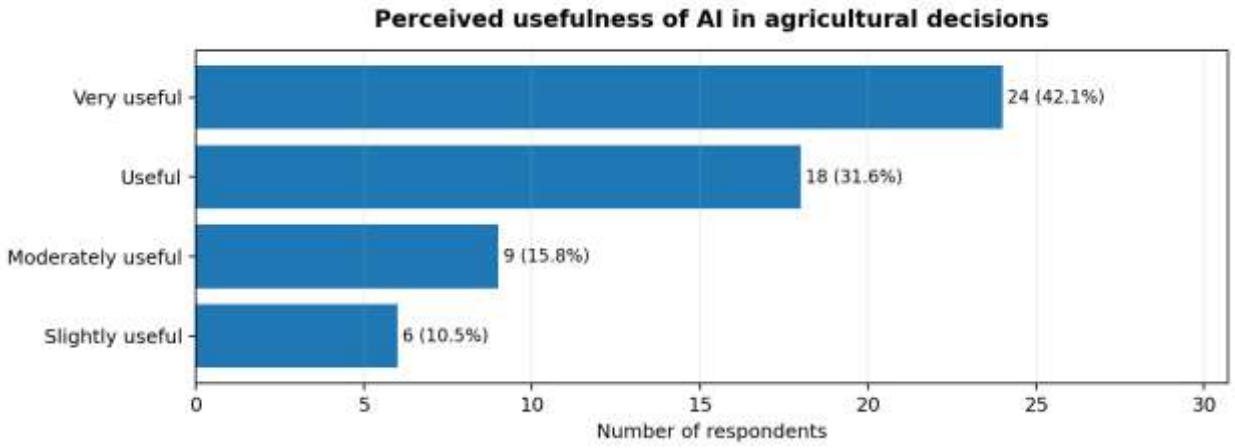


Figure 2. Usefulness

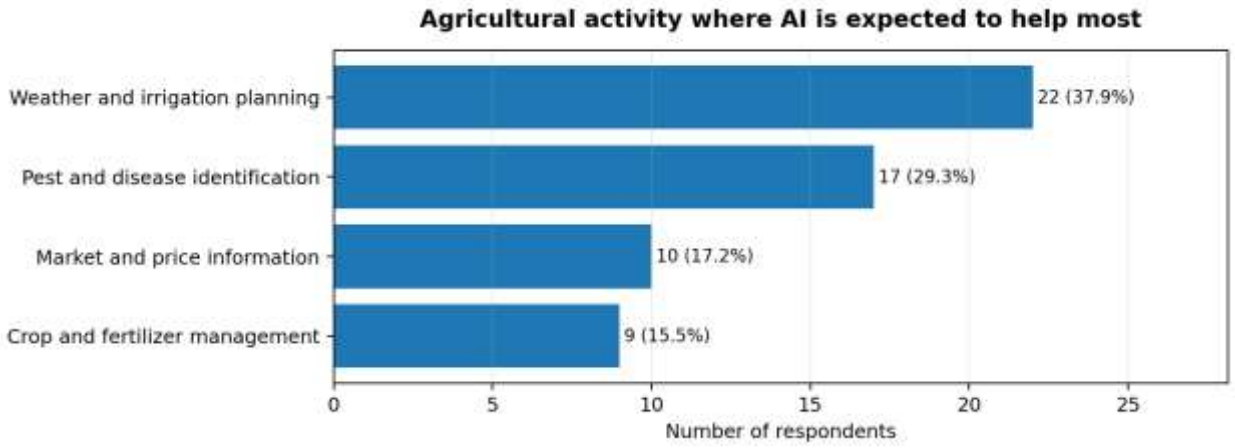


Figure 3. Ai Activity

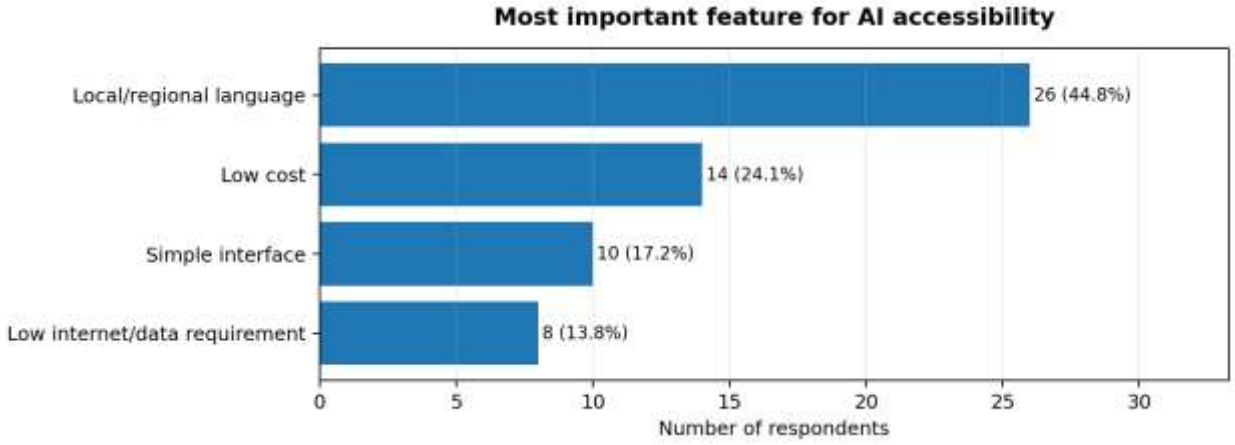


Figure 4. Accessibility

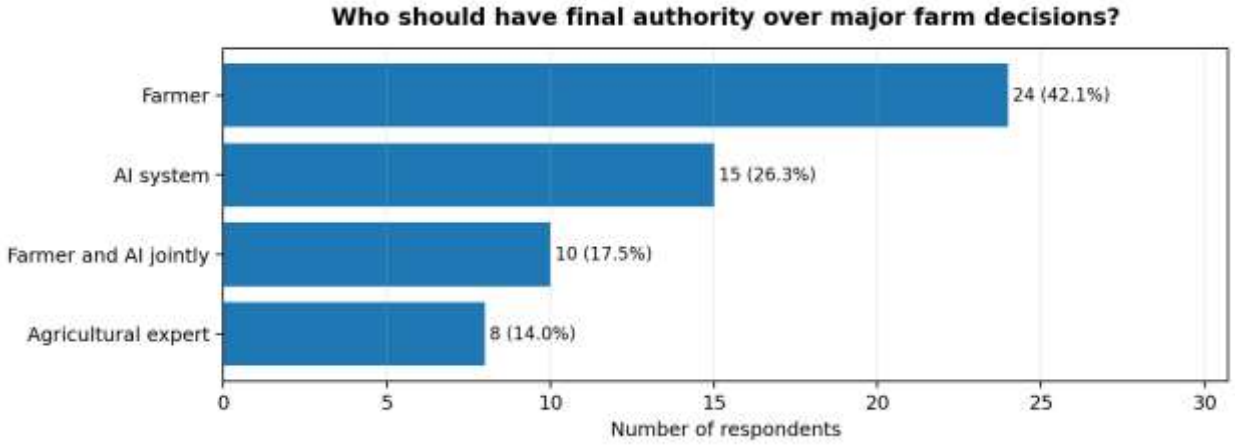


Figure 5. Authority

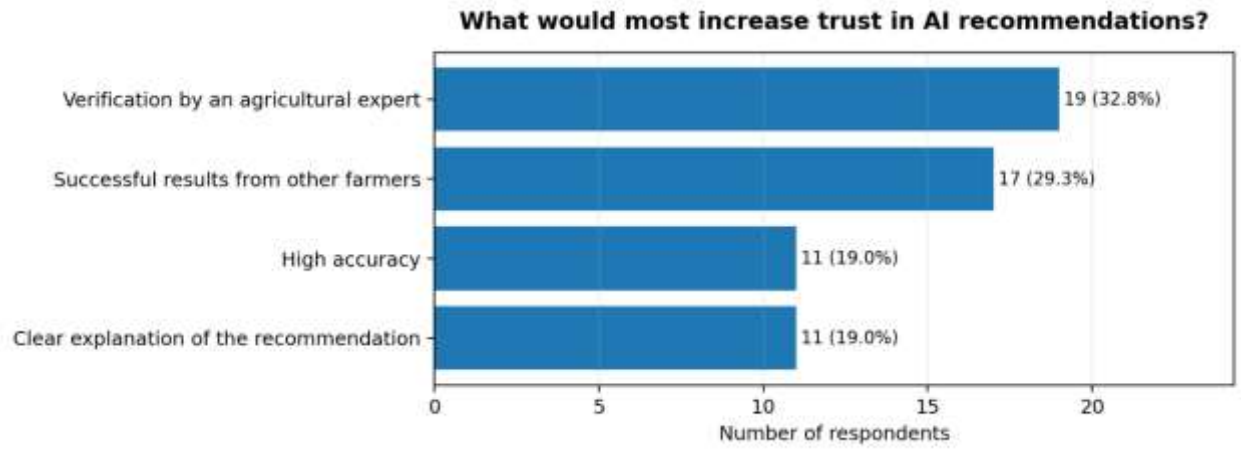


Figure 6. Trust

4. Frequency and percentage tables

The following tables cover every questionnaire item. N varies because some respondents skipped individual questions.

Table 1. What is your age group?

Response category	Frequency (n)	Percentage (%)
Below 25 years	56	93.3
25–35 years	3	5.0
36–45 years	1	1.7

Valid responses: 60 | Missing responses: 1. Most selected response: “Below 25 years” (56; 93.3%).

Table 2. What is your gender?

Response category	Frequency (n)	Percentage (%)
Male	34	56.7
Female	26	43.3

Valid responses: 60 | Missing responses: 1. Most selected response: “Male” (34; 56.7%).

Table 3. What is your highest level of education?

Response category	Frequency (n)	Percentage (%)
Graduate	32	54.2
Secondary education	12	20.3
Postgraduate or above	8	13.6
No formal education	7	11.9

Valid responses: 59 | Missing responses: 2. Most selected response: “Graduate” (32; 54.2%).

Table 4. How many years of farming experience do you have?

Response category	Frequency (n)	Percentage (%)
Less than 5 years	47	82.5
5–10 years	5	8.8
11–20 years	4	7.0
More than 30 years	1	1.8

Valid responses: 57 | Missing responses: 4. Most selected response: “Less than 5 years” (47; 82.5%).

Table 5. What is the approximate size of your farm?

Response category	Frequency (n)	Percentage (%)
Less than 1 acre	30	54.5
1 - 2 acres	12	21.8
More than 10 acres	6	10.9
2 -5 acres	5	9.1
5 - 10 acres	2	3.6

Valid responses: 55 | Missing responses: 6. Most selected response: “Less than 1 acre” (30; 54.5%).

Table 6. What type of farming do you mainly practice?

Response category	Frequency (n)	Percentage (%)
Crop farming	36	63.2
Mixed farming	17	29.8
Livestock/dairy	4	7.0

Valid responses: 57 | Missing responses: 4. Most selected response: “Crop farming” (36; 63.2%).

Table 7. What is your level of access to digital technology?

Response category	Frequency (n)	Percentage (%)
Smartphone with regular internet	40	69.0
Smartphone with limited internet	10	17.2
Access to a family member's smartphone	4	6.9
Basic mobile phone only	4	6.9

Valid responses: 58 | Missing responses: 3. Most selected response: “Smartphone with regular internet” (40; 69.0%).

Table 8. Have you previously used any digital agricultural service?

Response category	Frequency (n)	Percentage (%)
No	26	44.8
Yes, occasionally	19	32.8
Yes, regularly	10	17.2
Tried once or twice	3	5.2

Valid responses: 58 | Missing responses: 3. Most selected response: "No" (26; 44.8%).

Table 9. How familiar are you with Artificial Intelligence (AI) in agriculture?

Response category	Frequency (n)	Percentage (%)
Somewhat familiar	22	37.9
Heard about it but know very little	18	31.0
Very familiar	15	25.9
Only know the term AI	3	5.2

Valid responses: 58 | Missing responses: 3. Most selected response: "Somewhat familiar" (22; 37.9%).

Table 10. Which agricultural activity do you think AI can support most effectively?

Response category	Frequency (n)	Percentage (%)
Weather and irrigation planning	22	37.9
Pest and disease identification	17	29.3
Market and price information	10	17.2
Crop and fertilizer management	9	15.5

Valid responses: 58 | Missing responses: 3. Most selected response: "Weather and irrigation planning" (22; 37.9%).

Table 11. What type of AI-based agricultural information would be most useful to you?

Response category	Frequency (n)	Percentage (%)
Pest and disease alerts	20	34.5
Weather forecasts	19	32.8
Market prices	13	22.4
Irrigation recommendations	6	10.3

Valid responses: 58 | Missing responses: 3. Most selected response: "Pest and disease alerts" (20; 34.5%).

Table 12. How useful do you think AI could be for improving agricultural decisions?

Response category	Frequency (n)	Percentage (%)
Very useful	24	42.1
Useful	18	31.6
Moderately useful	9	15.8
Slightly useful	6	10.5

Valid responses: 57 | Missing responses: 4. Most selected response: "Very useful" (24; 42.1%).

Table 13. Which benefit of AI would be most important to you?

Response category	Frequency (n)	Percentage (%)
Early identification of crop problems	29	50.0
Better use of water and fertilizer	12	20.7

Better weather-related decisions	11	19.0
Better market decisions	6	10.3

Valid responses: 58 | Missing responses: 3. Most selected response: "Early identification of crop problems" (29; 50.0%).

Table 14. If AI provides an agricultural recommendation, what should the farmer be able to do?

Response category	Frequency (n)	Percentage (%)
Modify it according to local conditions	24	41.4
Follow it automatically	13	22.4
Accept or reject it	12	20.7
Discuss it with an expert before deciding	9	15.5

Valid responses: 58 | Missing responses: 3. Most selected response: "Modify it according to local conditions" (24; 41.4%).

Table 15. What would make you trust an AI agricultural recommendation most?

Response category	Frequency (n)	Percentage (%)
Verification by an agricultural expert	19	32.8
Successful results from other farmers	17	29.3
High accuracy	11	19.0
Clear explanation of the recommendation	11	19.0

Valid responses: 58 | Missing responses: 3. Most selected response: "Verification by an agricultural expert" (19; 32.8%).

Table 16. If an AI recommends a particular action, how much explanation would you want?

Response category	Frequency (n)	Percentage (%)
A detailed technical explanation	23	39.7
A simple explanation in local language	16	27.6
Main reason and expected benefit	15	25.9
No explanation required	4	6.9

Valid responses: 58 | Missing responses: 3. Most selected response: "A detailed technical explanation" (23; 39.7%).

Table 17. If an AI recommendation conflicts with your farming experience, what would you do?

Response category	Frequency (n)	Percentage (%)
Follow the AI recommendation	19	33.3
Consult an agricultural expert	13	22.8
Compare both and then decide	13	22.8

Follow my own experience	12	21.1

Valid responses: 57 | Missing responses: 4. Most selected response: “Follow the AI recommendation” (19; 33.3%).

Table 18. Who should have the final authority over major agricultural decisions?

Response category	Frequency (n)	Percentage (%)
Farmer	24	42.1
AI system	15	26.3
Farmer and AI jointly	10	17.5
Agricultural expert	8	14.0

Valid responses: 57 | Missing responses: 4. Most selected response: “Farmer” (24; 42.1%).

Table 19. How should AI use farmers' local knowledge and experience?

Response category	Frequency (n)	Percentage (%)
It should consider local knowledge as additional information	19	33.3
All of the above	15	26.3
It should not use local knowledge	12	21.1
It should allow farmers to correct AI recommendations	11	19.3

Valid responses: 57 | Missing responses: 4. Most selected response: “It should consider local knowledge as additional information” (19; 33.3%).

Table 20. Which feature is most important for making agricultural AI accessible to farmers?

Response category	Frequency (n)	Percentage (%)
Local/regional language	26	44.8
Low cost	14	24.1
Simple interface	10	17.2
Low internet/data requirement	8	13.8

Valid responses: 58 | Missing responses: 3. Most selected response: “Local/regional language” (26; 44.8%).

Table 21. How would you prefer to receive AI-based agricultural advice?

Response category	Frequency (n)	Percentage (%)
Mobile application	25	43.1
Voice-based service	11	19.0
WhatsApp/SMS	11	19.0
Agricultural extension worker	11	19.0

Valid responses: 58 | Missing responses: 3. Most selected response: “Mobile application” (25; 43.1%).

Table 22. Which climate-related challenge could AI help you manage most effectively?

Response category	Frequency (n)	Percentage (%)
All of the above	24	41.4
Excess rainfall/flooding	18	31.0
Drought and water shortage	15	25.9
Extreme temperature	1	1.7

Valid responses: 58 | Missing responses: 3. Most selected response: "All of the above" (24; 41.4%).

Table 23. If an AI agricultural service is affordable, reliable, available in your local language and allows you to retain final decision-making authority, how likely would you be to use it?

Response category	Frequency (n)	Percentage (%)
Very likely	29	50.0
Likely	26	44.8
Neutral/Not sure	3	5.2

Valid responses: 58 | Missing responses: 3. Most selected response: "Very likely" (29; 50.0%).

5. Chi-square tests of association

Chi-square tests assess whether two categorical variables are associated. For clarity and to reduce sparse cells, the variables below were grouped into two categories before testing.

Chi-square: Prior digital agricultural service use vs perceived usefulness

Usefulness was grouped as "Useful/Very useful" versus "Moderately/Slightly useful"; digital experience was grouped as "Any prior use" versus "No prior use".

Comparison	χ^2	df	p-value
Prior digital agricultural service use vs perceived usefulness	4.880	1	0.027

Contingency table (counts):

Group	Useful / Very useful	Moderately / Slightly useful
Any prior use	27	4
No prior use	15	11

Minimum expected cell count: 6.84. Expected counts are acceptable for the usual chi-square approximation.

Interpretation: The association is statistically significant at the 5% level ($p = 0.027$). In this sample, 27 of 31 respondents with some prior digital agricultural service use rated AI as useful/very useful, compared with 15 of 26 respondents with no prior use. This indicates an association, not proof that prior use causes higher usefulness ratings.

Chi-square: AI familiarity vs perceived usefulness

AI familiarity was grouped as "Somewhat/Very familiar" versus "Limited familiarity"; usefulness grouping is the same as above.

Comparison	χ^2	df	p-value
AI familiarity vs perceived usefulness	1.515	1	0.218

Contingency table (counts):

Group	Useful / Very useful	Moderately / Slightly useful
Somewhat / Very familiar	29	7
Limited familiarity	13	8

Minimum expected cell count: 5.53. Expected counts are acceptable for the usual chi-square approximation.

Interpretation: The association is not statistically significant at the 5% level (p = 0.218). The data do not provide sufficient evidence of an association between these grouped familiarity and usefulness categories in this sample.

6. One-way ANOVA tests (exploratory)

ANOVA compares average numeric scores across groups. The questionnaire responses are ordinal categories, not continuous measurements; therefore, scores were assigned only for exploratory analysis. These ANOVA results should be interpreted cautiously and ideally supported by ordinal regression or non-parametric tests in a publication-ready study.

Outcome score	Grouping variable	F statistic	p-value	Decision at 0.05
Adoption intention (Neutral=1, Likely=2, Very likely=3)	AI familiarity (4 original groups)	1.056	0.375	Not significant
Usefulness (Slightly=1 to Very useful=4)	Prior digital service use (4 original groups)	3.468	0.022	Significant*

ANOVA 1 interpretation: Adoption-intention scores did not differ significantly across the four AI-familiarity groups, F = 1.056, p = 0.375. The sample does not show statistically significant mean-score differences by familiarity level.

ANOVA 2 interpretation: Usefulness scores differed across prior digital-service-use groups, F = 3.468, p = 0.022. Respondents who reported regular use had the highest average usefulness score, but one category has only three respondents and the outcome is ordinal. Treat this as exploratory rather than definitive evidence.

*Statistical significance is not the same as practical importance. Assumptions such as independent observations, approximate normality of residuals and comparable variances should be checked before formal publication.

7. Main findings

- The sample is young: 56 of 60 valid age responses (93.3%) were below 25 years.
- Smartphones with regular internet were the most commonly reported digital access option (40 of 58; 69.0%).
- Weather and irrigation planning was the most selected agricultural activity for AI support (22 of 58; 37.9%).
- AI was rated useful or very useful by 42 of 57 respondents (73.7%).
- Early identification of crop problems was the leading expected benefit (29 of 58; 50.0%).
- The most common preference was to modify AI recommendations according to local conditions (24 of 58; 41.4%).
- Expert verification was the most frequently selected trust signal (19 of 58; 32.8%).
- Local/regional language was the most frequently selected accessibility feature (26 of 58; 44.8%).

- 55 of 58 respondents (94.8%) were likely or very likely to use an AI service if it were affordable, reliable, available in their local language and preserved their decision authority.
- Chi-square analysis found an association between prior digital-service use and grouped usefulness ratings; the familiarity-usefulness association was not significant.
- The ANOVA results are exploratory because the response scores are ordinal and some group sizes are small.

8. Conclusion and recommendations

The descriptive results show a generally positive orientation toward AI-supported agriculture in this respondent group. The strongest priorities are early crop-problem identification, weather and irrigation planning, expert verification, local-language access and the ability of farmers to review or modify AI recommendations. These results are consistent with a farmer-centred human–AI collaboration approach, but they do not establish that AI will improve farm outcomes.

Recommendations: (1) provide regional-language and low-bandwidth services; (2) include clear explanations and expert verification; (3) preserve farmer authority to accept, modify or reject recommendations; (4) collect a larger and more representative sample, especially including experienced farmers; and (5) predefine multi-item scales for usefulness, trust, explainability, autonomy and adoption intention before testing the full conceptual model.

9. Statistical reporting note

The chi-square and ANOVA tests above were calculated from the 61-row raw survey spreadsheet. Chi-square tests use grouped categorical variables to avoid highly sparse contingency tables. ANOVA uses numeric scores assigned to ordinal categories and is therefore exploratory. These tests do not directly test every hypothesis in the paper; construct-level hypothesis testing requires suitable multi-item measures and a documented analysis plan.

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21. PROPOSED NOVEL FRAMEWORK: FHACF-2035

The FHACF-2035 framework explains how AI and farmers can work together in agricultural decision-making:

OBSERVE → ANALYSE → RECOMMEND → EXPLAIN → HUMAN REVIEW → DECIDE → LEARN

- **Observe:** AI identifies crop conditions, patterns and risks.
- **Analyse:** AI analyses the collected information.
- **Recommend:** AI suggests suitable actions.
- **Explain:** AI clearly explains the reason and evidence behind its recommendation.
- **Human Review:** Farmers evaluate the recommendation using their experience and local knowledge.
- **Decide:** Farmers accept, modify or reject the recommendation and make the final decision.
- **Learn:** AI uses feedback and outcomes to improve future recommendations.

Clarity is important at every stage. AI should provide information and recommendations in a **simple, understandable and transparent way**, while the farmer retains **control and final decision-making authority.**

22. PROPOSED HUMAN-AI ROLE DISTRIBUTION

Agricultural Function AI Role Human Role
Weather analysis Predict Interpret local conditions
Pest identification Detect Verify field conditions
Irrigation Recommend Decide

Crop selection Compare options Consider local experience
Disease detection Identify possible disease Confirm and act
Market information Analyse trends Decide selling strategy
Climate risk Generate warning Select response
Farm planning Simulate alternatives Choose final plan
This framework proposes that AI is not an independent decision-maker.

23. EXPECTED FINDINGS

This study expects to find that:
1. Farmers see potential value in adopting AI-supported agricultural services.
2. Trust is a critical factor affecting farmers' adoption intentions.
3. Explainability affects the extent to which farmers can trust AI.
4. Farmers prefer to retain autonomy over major farm decisions.
5. Local language support is an important consideration for agricultural AI.
6. Affordable and low-connectivity AI systems are likely to be prioritized by small-scale farmers.
7. Farmers see value in using AI to respond to climate risks.
8. The combination of human and AI decision-making is more acceptable than full automation.
These are expected findings, not actual survey results.

24. CURRENT REAL-WORLD EVIDENCE RELEVANT TO THE STUDY

The proposed study is timely given the current evidence on agricultural AI. India's Ministry of Agriculture and Farmers Welfare reports applications of AI in farmer advisory, pest control, crop identification, insurance, schemes and governance. Its National Pest Surveillance System uses AI and machine learning for pest surveillance and has been deployed by more than 10,000 extension workers. Recent World Bank evidence highlights the emergence of Indian "small AI" as a means of providing crop, pest, weather, market and government-related information to farmers through accessible interfaces. FAO's 2026 work plan prioritizes responsible, inclusive and scalable agricultural AI, with a specific focus on farmers' needs, data governance, climate resilience and so on. The World Bank's own agricultural AI research lists use cases in farm management, pest identification, precision agriculture, weather forecasting, market systems and climate-risk management, while emphasizing the importance of infrastructure, skills, governance and inclusion. All of this evidence reinforces the need to think beyond AI capabilities and consider the human-AI collaboration landscape.

25. DISCUSSION

The main point of this study is to argue that agricultural AI should be regarded as a collaborative decision-support technology. In other words, farmers have contextual intelligence, while AI has computational intelligence. The two forms of intelligence can be combined for better decisions. An example is an AI recommendation for pest control. The AI recommendation can indicate the likelihood of infestation based on an image, while the farmer can combine this information with their knowledge about the economic importance of the crop, actual pest presence in the field and the affordability of pesticide. In this sense:
AI serves to extend farmers' information-handling capabilities, but farmers retain their responsibility for making decisions based on their judgement and circumstances. This is especially important for smallholder farming, where farm management decisions are influenced by a range of economic, environmental and social factors.

26. PRACTICAL IMPLICATIONS

For Farmers
Agro-AI services should be:
• Affordable
• Simple

• Local language-friendly
• Explainable
• Accessible to low-end smartphones
• Functional under low connectivity

For Government

Agricultural AI policies should consider:

• Data protection
• Interoperability
• Farmer participation
• Digital literacy
• Public data infrastructure
• Independent evaluations

For Agritech Companies

Agro-AI developers should focus on:

• Local data
• Explainability
• Farmer feedback
• Low-bandwidth systems
• Multilingual interfaces
• Transparent data practices

For Agricultural Extension

Extension workers can play a critical role in mediating between farmers and AI.

27. LIMITATIONS

1. The findings will be limited by the representativeness of the sample.
2. Farmer perceptions of AI can change over time.
3. Access to AI varies between different agricultural settings.
4. Self-reported attitudes may not reflect actual behaviour.
5. AI recommendations are only as good as the data they are trained on.
6. A sample size of 300 cannot represent the views of all farmers in India.

28. FUTURE RESEARCH

Future researchers can go beyond surveys and experiment with crop seasons. One particularly promising design is to contrast three treatment groups:

Group A: Traditional farming – no AI

Group B: AI-supported farming – no human-AI collaboration

Group C: Human-AI collaborative farming

The three groups can then be compared using outcome variables such as:

• Yield
• Cost of production
• Water use
• Fertilizer use
• Pest losses
• Time of decision-making
• Farmer satisfaction
• Household income
• AI trust
• Accuracy of AI recommendations

This can allow future researchers to go from perception to reality.

29. CONCLUSION

The farming system of 2035 will not be dominated by robots and will not be traditional either. Rather, it will be more transformative to consider how human agricultural intelligence can be combined with artificial intelligence. This study proposes the FHACF-2035 framework in which AI observes, analyses, predicts and explains, while farmers review, decide and act. There is one overarching principle that guides this framework, namely, that AI should enhance the decision-making capacity of the farmer instead of deprecating the farmer's role in the decision-making process. Current developments in India and elsewhere demonstrate that agricultural AI is already entering the realm of practical applications in terms of pest surveillance, farmer advisory services, crop intelligence, weather information and digital agriculture. The next frontier is to transition from better technology to better technology-farmer relations. For 2035 agriculture, this implies a new paradigm of intelligence + human agency + explainability + accessibility + responsibility + climate resilience. The proposed human-AI collaboration framework can serve as a foundation for building such a paradigm.

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