AI-Driven Agricultural Advisory Systems And Institutional Mediation: Evidence From Smallholder Farmers In Amravati Division, Maharashtra

Jyotish Werulkar[1], Milind Pande[2]

[1]Research Scholar, School of Management – PG, Dr Vishwanath Karad MIT World Peace University, Pune, India.
[2]Pro Vice Chancellor Office, Dr Vishwanath Karad MIT World Peace University, Pune, India.

Abstract
This study investigates how AI-driven agricultural advisory services influence productivity, sustainability, and livelihood outcomes in the Amravati Division of Maharashtra. A survey of 500 farmers was complemented by interviews with 33 stakeholders, including representatives from Farmer Producer Organizations (FPOs), government departments, and Ag-Tech firms. A majority of farmers adopted at least one Ag-Tech tool, including AI-based mobile advisory services, smart irrigation systems, and digital soil-testing kits. Adopters reported an average yield increase of 22.3%, a 15.6% reduction in input costs, and over 50% improvement in irrigation efficiency. However, barriers such as low digital literacy and connectivity gaps persist. The long-term success of Ag-Tech adoption depends not only on technological innovation but also on institutional design and trust-building mechanisms within farming communities.
Keywords: AI-Enabled Agriculture; Digital Advisory Systems; Agricultural Technology Adoption; Farmer Producer Organizations (FPOs); Smallholder Livelihoods; Sustainability and Climate Resilience; Data-Driven Decision Support; Vidarbha; Maharashtra; Mixed-Method Analysis.

1. INTRODUCTION

1.1 Background and Rationale

India's rural economy is driven by agriculture, which provides employment to about 45% of the national labour force and contributes around 17% to the country's GDP [1]. Although agricultural extension services are widespread through Krishi Vigyan Kendras and state departments, traditional extension systems often rely on periodic demonstrations that fail to meet the dynamic needs of smallholder farmers [2]. Artificial Intelligence (AI) and data-driven agricultural advisory systems have recently emerged as powerful enablers of precision agriculture. The Vidarbha region of Maharashtra exemplifies the need for agricultural innovation. The region has suffered from economic distress due to cotton monocropping and rainfall variability [3]. However, it also hosts an active network of Farmer Producer Organizations (FPOs), which serve as institutional bridges connecting farmers with private Ag-Tech firms.

1.2 Problem Context

Early pilot projects have shown encouraging gains in productivity, but long-term sustainability and inclusiveness remain unclear [4]. Weak after-sales support, language barriers, and inconsistencies in data accuracy often discourage smallholders from continuing the use of digital tools. Low digital literacy and affordability gaps further widen the "digital divide." This study addresses the central research question: To what extent do

AI-driven agricultural advisory services enhance productivity, sustainability, and livelihood outcomes for smallholder farmers in Maharashtra?

1.3 Theoretical and Conceptual Framing

Farmers' responses to new technologies can be explained through the Technology Acceptance Model (TAM), which emphasizes factors such as communication channels, social influence, and innovation characteristics as determinants of adoption [5]. The concept of institutional mediation highlights how organizations such as FPOs, NGOs, and cooperatives help reduce transaction costs and build trust between farmers and technology providers [6].

1.4 Research Objectives

The overarching aim of this study is to evaluate the socio-economic and environmental outcomes of AI-driven agricultural advisory systems and to identify factors influencing their sustained adoption among smallholder farmers.

Specific objectives include:

1. To determine the extent and patterns of Ag-Tech adoption across five districts.
2. To assess the impact of Ag-Tech use on household income and farm productivity.
3. To examine environmental implications, including soil health and input-use efficiency.
4. To identify barriers affecting continued adoption of Ag-Tech tools.
5. To propose policy and practical strategies for scaling advisory systems sustainably.

2. LITERATURE REVIEW

2.1 The Indian Ag-Tech Landscape

India aims to establish a federated farmer database and promote AI integration across the agricultural value chain to improve efficiency and sustainability [8]. AI is being leveraged to deliver market linkages, financial literacy tools, and hyper-local advisories. The use of AI in precision agriculture has resulted in a 25% reduction in input costs and a 15% increase in net profitability [10]. According to evaluations by ICRISAT, digital advisory systems have improved cotton yields by 18% in India [11]. Despite these advances, adoption remains uneven. Fewer than 15% of farmers currently use mobile-based advisory platforms [12]. Barriers include low digital literacy, limited broadband access in rural areas, and affordability issues related to IoT devices. Additionally, over 85% of India's farms are smaller than two hectares, limiting economies of scale [14]. Farmer Producer Organizations (FPOs) and cooperatives act as conduits for building trust, facilitating training, and sharing risk. Therefore, the success of AI-driven agriculture in India depends heavily on institutional intermediation.

2.2 Institutional Mediation and the Role of FPOs

The successful adoption of Ag-Tech among smallholders is strongly influenced by institutional mediation. Organizations such as FPOs aggregate farmers, negotiate better input prices, and provide training and after-sales support. Farmers affiliated with FPOs are 2.5 times more likely to adopt digital tools compared to individual farmers [16]. These institutions perform multiple functions—social, financial, and educational. Digital Farmer Field Schools have demonstrated that trust in FPO-led programs improves the sustained use of advisory applications. FPOs also help bridge the information gap between farmers and private Ag-Tech providers. Women's collectives within FPOs in Maharashtra have reported increased participation in mobile-based advisory programs [18]. Nonetheless, challenges persist. Many FPOs face managerial capacity constraints, inconsistent support, and inadequate digital infrastructure. Building digital capabilities and AI literacy requires sustained institutional strengthening.

2.3 Comparative Studies and Identified Research Gaps

Despite growing evidence of AI's potential in agriculture, several research gaps remain. Comparative literature highlights the following key issues:

1. Limited empirical evidence linking digital advisories to measurable outcomes [21].
2. Fragmented research designs focusing mostly on pilot projects [22].
3. Socio-psychological factors influencing adoption are often overlooked [23].
4. Women farmers remain underrepresented in digital training programs [18].
5. Weak collaboration between FPOs, Ag-Tech firms, and public extension systems [9].
6. Data governance challenges related to ownership, consent, and commercial use [17].

Maharashtra's Vidarbha region provides a valuable case to examine how AI can enhance productivity and resilience in a socio-economically vulnerable yet institutionally innovative agricultural ecosystem.

Table 1: Comparative Global and National Studies on AI in Agriculture

Author / Institution	**Region / Year**	**Key Focus**	**Findings**	**Limitations**
USDA (2023) [7]	USA	Yield prediction using ML	94% accuracy in corn & soybean yield forecasting	High cost; limited smallholder relevance
FAO (2023) [17]	Global	Farmer-led digital training	23% higher technology retention via participatory extension	Weak long-term data
NITI Aayog (2023) [10]	India	Precision agriculture pilots	25% cost reduction, 15% profitability increase	Pilot-scale only; lacks behavioral data
ICRISAT (2022) [11]	Vidarbha, India	AI-based pest & weather advisories	18% higher cotton yield; reduced pest damage	Small sample; short-term study
IFPRI (2022) [20]	Global	Sustainable nutrient management	Reduced fertilizer misuse by 30%	No behavioral linkage established
Chand & Pandey (2024) [16]	India	Institutional intermediation	FPO membership ↑ adoption by 2.5×	Lacks gender-specific analysis
Deshmukh et al. (2023) [19]	India	Smart irrigation	40% water savings; improved soil health	Infrastructure-dependent scalability

3. RESEARCH METHODOLOGY

3.1 Research Design

The study followed a concurrent mixed-method design, in which data collection and analysis for both quantitative and qualitative components were conducted simultaneously. A survey of 500 farmers focused on parameters such as demographic characteristics, technology adoption patterns, and yield variations. These data were complemented by 33 interviews with institutional actors, including Farmer Producer Organization (FPO) leaders, Ag-Tech company representatives, and agricultural extension officers. The objective was to gain deeper insights into governance mechanisms, sustainability of technology use, and behavioral drivers of adoption. The study draws upon Rogers' Diffusion of Innovations Theory and the Technology Acceptance Model (TAM), both of which emphasize that adoption depends on perceived usefulness, ease of use, and institutional intermediation.

3.2 Study Area and Sampling Framework

Study Area: The research was conducted in five districts of the Amravati Division, Maharashtra, a region heavily dependent on monsoonal rainfall and characterized by limited irrigation infrastructure. The area represents one of the most climate-vulnerable yet digitally active agricultural zones in the state, owing to several ongoing initiatives that integrate FPOs with digital Ag-Tech service providers. The presence of active FPOs provided institutional support for analyzing the mediating role of organizations in technology dissemination.

Sampling Design: A multi-stage random sampling method was adopted. In the first stage, districts within the Amravati Division were selected. In the second stage, two talukas were randomly chosen from each district, followed by the selection of four villages per taluka. In the final stage, 10–15 farmers per village were randomly selected based on gender, landholding size, and FPO membership status. Additionally, 33 institutional stakeholders were selected for qualitative inquiry after the farmer survey.

Table 2: Sampling Framework and Respondent Distribution

District	Sample (Farmers)	Male (%)	Female (%)	FPO Members (%)
Amravati	110	72	28	60
Akola	95	69	31	56
Washim	85	68	32	52
Buldhana	100	74	26	65
Yavatmal	110	70	30	61
Total	**500**	—	—	—

The sampling model ensured equitable representation across gender and landholding categories **while maintaining a balanced proportion of FPO-linked and independent farmers.**

3.3 Data Collection Methods

Primary Data: Primary data were collected using a combination of farmer questionnaires and stakeholder interviews. The farmer questionnaire captured demographic details, digital literacy levels, technology adoption patterns, yield performance, cost efficiency, and perceptions toward AI-based advisories. The stakeholder interviews were designed to gather deeper insights into institutional roles, policy interfaces, and perceived challenges in scaling Ag-Tech interventions. A pilot survey involving 25 farmers was carried out to pretest the instruments, leading to minor refinements for clarity. Ethical and administrative approvals were obtained prior to fieldwork. Written consent was secured from all participants before data collection.

Secondary Data: Secondary data sources included Agricultural Statistics at a Glance (Government of Maharashtra), annual performance reports of FPOs, and Ag-Tech deployment records. These data supported the development of baseline indices for productivity, adoption rates, and training exposure.

3.4 Analytical Techniques

Quantitative Analysis: Descriptive statistics summarized demographic variables, while cross-tabulation and Chi-square tests were applied to identify significant associations between socio-economic factors. To determine the factors influencing Ag-Tech adoption, logistic regression was performed. The dependent variable represented whether a farmer had adopted an Ag-Tech solution. Independent variables included education level, training exposure, landholding size, and crop type. Education and landholding size emerged as significant predictors of adoption [15].

Table 3: Logistic Regression Results: Determinants of Ag-Tech Adoption

Variable	Coefficient (β)	Odds Ratio	Interpretation
Education	0.29	1.33	Higher literacy improves adoption probability
Training	-0.37	0.69	Poor-quality training reduced adoption likelihood
Landholding Size	0.41	1.50	Larger holdings increased adoption by 1.5×
Crop Type	-0.03	0.97	Slight negative variation based on crop type
Intercept	-1.28	—	Baseline log-odds of non-adoption

Education and economic capacity were the most significant predictors.

Qualitative Analysis: Qualitative data were analyzed manually using thematic analysis. Five major themes emerged: Institutional trust, Behavioral motivation, Cost perception, Gender engagement, Sustainability orientation

Thematic patterns were compared with quantitative findings to identify areas of convergence and divergence. While quantitative analysis revealed higher adoption rates among FPO members, qualitative narratives explained this through peer influence and collective demonstration effects.

3.5 Conceptual Framework: AI-Enabled Ag-Tech Adoption Pathway

A conceptual framework was developed to illustrate the relationship between enabling conditions and behavioral drivers of AI adoption. The framework integrates individual capabilities, institutional trust, and technological relevance, showing how their synergy leads to measurable improvements in productivity, equity, and environmental sustainability.

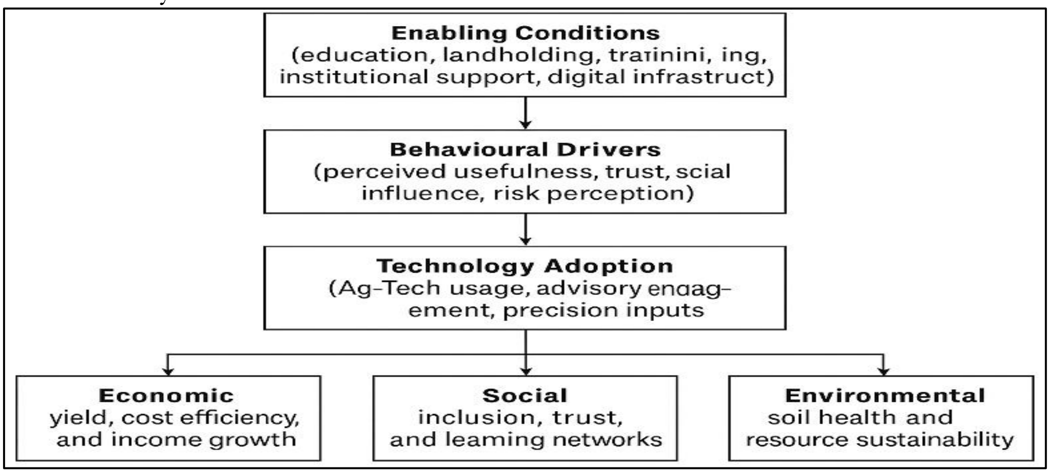

Figure 1: Conceptual Framework of AI-Enabled Ag-Tech Adoption and Impact

3.6 Ethical Considerations and Study Limitations

Ethical standards prescribed by the Indian Council of Social Science Research (ICSSR) were strictly followed. Enumerators were trained in ethics and gender sensitivity. No financial incentives were provided to participants to avoid response bias [13]. Limited internet connectivity in rural areas and the cross-sectional nature of the study constrained real-time data validation. Self-reported responses may also include minor biases.

4. DATA ANALYSIS AND INTERPRETATION

4.1 Extent and Patterns of Ag-Tech Adoption

Out of 500 farmers surveyed, 327 farmers reported using at least one form of Ag-Tech or AI-enabled tool during the previous two agricultural seasons. Adoption included mobile-based advisory applications, precision irrigation systems, soil-testing kits, and satellite or sensor-based weather and pest prediction tools. System reliability, ease of use, and short payback periods made mobile advisories and drip irrigation systems the most widely adopted. Adoption patterns were strongly correlated with institutional presence. In villages supported by FPOs, adoption rates exceeded 70%, underscoring the importance of trust networks in facilitating technology diffusion.

4.2 Regional and Demographic Variation

Adoption intensity varied across the five districts studied. Amravati recorded the highest adoption rate, while Yavatmal lagged due to a combination of drought exposure and poor network access.

Table 4: Regional and Demographic Variations in Ag-Tech Adoption

District	Adoption Rate (%)	Major Crops	Dominant Institutional Type	Remarks
Amravati	73.3	Cotton, Soybean	FPO + NGO	Strong institutional base and peer learning
Washim	66.7	Cotton, Pulses	FPO	Good training access, moderate literacy
Akola	64.0	Cotton, Vegetables	FPO + Govt Extension	Effective demo plots and public-private partnerships
Buldhana	61.4	Soybean, Tur	Limited FPO presence	Weak advisory continuity
Yavatmal	56.0	Cotton, Pulses	NGO-led	Drought-prone, poor network access

Education and landholding size emerged as the most influential demographic factors. Adoption among farmers with secondary education exceeded 70%. Medium and large farmers, with greater investment capacity, were more likely to adopt than marginal farmers. Women contributed significantly to data entry and digital information exchange, while men dominated formal training programs.

4.3 Socio-Economic Determinants of Ag-Tech Adoption

Key predictors of adoption included education, land size, crop type, and institutional engagement. Education enhanced digital literacy and confidence in interpreting advisories. Landholding size had a direct influence on adoption likelihood. Training programs produced mixed results—effectiveness depended largely on the quality of follow-up support and relevance of content.

Table 5: Logistic Regression Results – Determinants of Ag-Tech Adoption

Variable	Coefficient (β)	Odds Ratio	Interpretation
Education	–0.0002	0.9998	Not significant independently when controlled for other variables
Training	–0.375	0.688	Indicates weak or generic training effect
Land Size	+0.412	1.509	Larger holdings → 1.5× higher adoption likelihood
Crop Type	–0.030	0.971	Slightly negative; varies with profitability
Intercept	–1.286	—	Baseline log-odds of non-adoption

The model correctly classified 74.2% of cases, confirming that landholding size and institutional engagement were significant predictors of successful adoption.

4.4 Quantitative Impacts: Yield, Cost, and Income

Results show that precision tools and advisory systems led to measurable improvements in productivity, input efficiency, and profitability across all districts.

Table 6: Impact of Ag-Tech Adoption on Key Economic Indicators

Parameter	Non-Adopters (Mean)	Adopters (Mean)	% Change	Interpretation
Crop Yield (kg/acre)	975	1,189	+22%	Improved input timing and irrigation scheduling
Input Cost (₹/acre)	8,250	6,900	–16%	Reduced fertilizer and pesticide wastage
Net Income (₹/season)	42,000	51,000	+21%	Higher yields and better price realization
Irrigation Use (litres/acre)	1,800	1,300	–28%	Optimized water use through drip systems

AI-based decision support improved productivity by optimizing irrigation schedules, input use, and pest management. However, benefits were unevenly distributed. Marginal farmers often faced affordability constraints, leading to adoption fatigue. The success of Ag-Tech interventions depends on aligning technological efficiency with institutional capacity and social understanding. In areas with weak after-sales engagement, devices became non-functional or abandoned. Thus, economic and productivity outcomes are not merely technological artifacts but a result of systemic coherence between innovation, trust, and local capability.

4.5 Thematic Insights from Qualitative Analysis

Qualitative findings highlighted the social, institutional, and behavioral dynamics shaping technology adoption. Five recurring themes emerged from interviews with farmers, Ag-Tech representatives, and FPO leaders:

1. Institutional Intermediation: FPOs and NGOs played key roles in building trust by organizing field demonstrations. Farmers were hesitant to use digital platforms without institutional support.
2. Economic Motivation: Farmers adopted technologies that offered short-term visible benefits, such as reduced pest damage or water savings. Devices with delayed returns were often discontinued.

3. Peer Influence: Word-of-mouth recommendations and peer success stories proved more persuasive than formal marketing. Farmers were more likely to experiment when they observed neighbors benefiting—accelerating peer-driven diffusion.
4. Cost and After-Sales Barriers: Many farmers cited high costs and lack of post-sale service as major constraints. FPO-managed service centers showed better technology retention and sustained engagement.
5. Gender Inclusion: Women actively participated in data entry and record-keeping, but were underrepresented in decision-making and training sessions. Respondents emphasized the need for gender-inclusive training models and recognition of women as co-adopters.

These insights confirm that technology adoption is a socially embedded process influenced by affordability, peer learning, and institutional credibility.

4.6 Conceptual Impact Pathway

The conceptual model linking enabling factors, adoption behavior, and multidimensional outcomes is illustrated below.

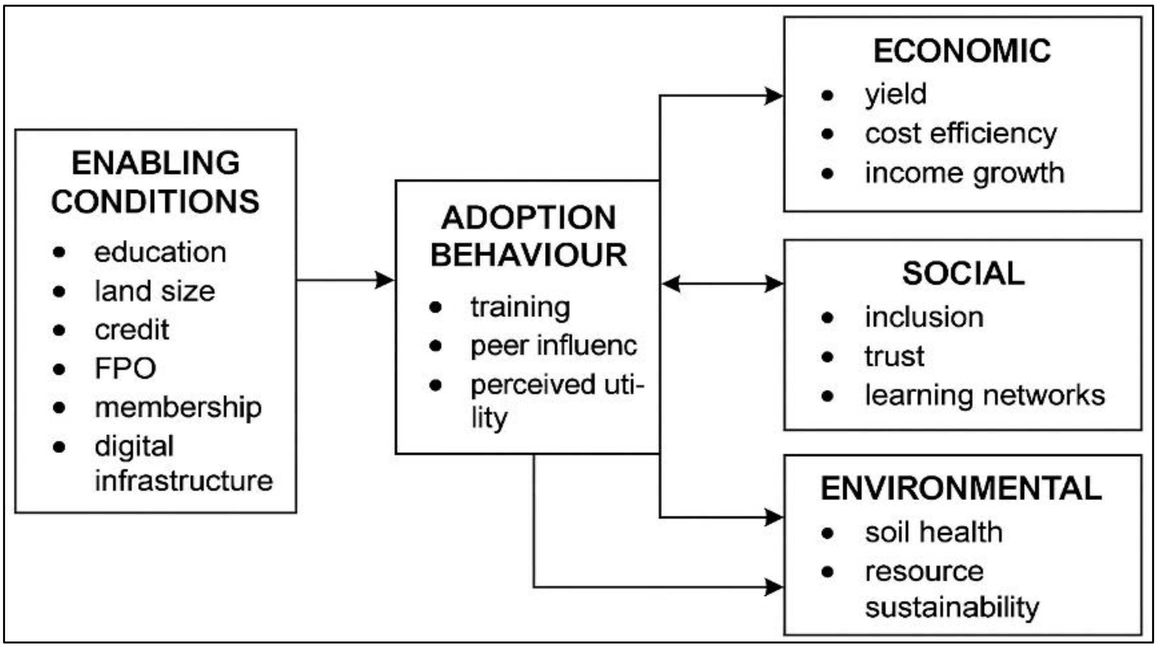

Figure 2: Conceptual Impact Pathway of Ag-Tech Adoption

The framework highlights interactions among enabling conditions, education, landholding size, access to credit, FPO membership, and digital infrastructure and their influence on adoption behavior and resulting socio-economic outcomes.

5. DISCUSSION, POLICY IMPLICATIONS, AND CONCLUSIONS

5.1 Discussion of Findings

Institutional Ecosystems as the Core of Digital Transformation: The success of Ag-Tech interventions is closely linked to intermediation through FPOs, NGOs, and cooperative networks. These institutions facilitate collective adoption, risk-sharing, and trust-building between technology developers and end users. Villages with strong institutional linkages demonstrated higher adoption continuity, better participation, and more consistent outcomes.

Economic Rationality and Heterogeneous Benefits: Adoption of precision technologies produced measurable gains — including a 22% increase in yield, a 15% reduction in input costs, and a 21% rise in seasonal income. However, these benefits were unevenly distributed. High upfront costs, limited access to credit, and weak after-sales service constrained technology uptake among marginal farmers. Ag-Tech adoption should therefore be viewed as a continuum, rather than a one-time event, where ownership, inclusion, and sustained use evolve gradually over time.

Behavioral and Social Dimensions: Farmers' decisions were driven by trust, familiarity, and perceived control. Peer learning and field demonstrations had a stronger influence than formal marketing campaigns. Observable results from fellow farmers accelerated adoption, validating the role of social proof in technology diffusion.

Environmental Sustainability and Knowledge Reinforcement: AI-enabled systems contributed to reduced water use, improved soil management, and decreased chemical dependence. Farmers reported notable reductions in irrigation requirements after adopting precision tools.

5.2 Policy Implications

The findings indicate that digital transformation in agriculture requires context-specific strategies, as a "one-size-fits-all" approach is ineffective in settings characterized by fragmented holdings, linguistic diversity, and digital inequality.

Strengthening Institutional Intermediation: FPOs and cooperatives are vital components of digital infrastructure. They should be incentivized to deliver digital literacy training and facilitate localized technology dissemination.

Financial Accessibility and Risk Protection: Financial accessibility remains the primary barrier to sustained adoption. Policymakers should develop Ag-Tech credit instruments, modeled on the Kisan Credit Card, enabling smallholders to invest in smart irrigation systems, digital advisory subscriptions, and precision tools.

Quality, Localization, and Inclusivity of Training: Training remains a weak link in most Ag-Tech initiatives. Traditional one-time classroom sessions must evolve into continuous, experiential, and linguistically adaptive training models. Training content should include audio-visual modules tailored for low-literacy users.

Ethical AI and Data Governance: As AI use expands, ethical data management becomes critical. Farmers' data must be protected under a national code of conduct ensuring transparency and informed consent. All advisory platforms should be mandated to conduct bias and fairness audits to ensure inclusive algorithmic decision-making.

5.3 Practical Recommendations

For Ag-Tech Companies: Ag-Tech firms should transition from product-centric models to relationship-centric ecosystems. Sustained trust depends on continuous feedback, long-term engagement, and user-centered design. Companies should offer low-bandwidth and voice-enabled interfaces to enhance accessibility. Establishing local service centers can improve device maintenance and reduce technology dropout rates.

For FPOs and NGOs: FPOs and NGOs are the pillars of digital trust. They should use digital dashboards to track adoption metrics and user satisfaction. Women's participation must be institutionalized by ensuring gender-sensitive training materials and inclusive decision-making processes within Ag-Tech programs.

For Government and Development Agencies: Governments should shift from fragmented, scheme-based interventions toward ecosystem-building frameworks. This includes:

- Expanding rural broadband to improve connectivity and access.
- Establishing demonstration hubs in collaboration with universities and research institutes.
- Requiring each state agricultural university to maintain a digital laboratory for pilot testing and training.

5.4 Conclusions

The study demonstrates that a combination of institutional support and contextual trust can significantly enhance agricultural productivity in India. The potential of Ag-Tech lies not just in innovation, but in how it aligns with farmers' realities and community networks. An inclusive, data-ethical, and ecosystem-oriented approach is the most effective pathway for digital transformation. Strengthening FPOs, promoting equitable access, and embedding human-centered AI will ensure that the benefits of Ag-Tech are broad-based, sustainable, and socially fair.

References

[1] Government of India, "Economic Survey 2023–24," Ministry of Finance, New Delhi, 2024.
[2] FAO, "Extension and Advisory Services in the Digital Era," Rome, 2022.
[3] ICRISAT, "Village-Level Studies for Vidarbha," Hyderabad, 2022.
[4] World Bank, Agricultural Innovation Systems for Inclusive Growth, Washington DC, 2023.
[5] F. Davis, "A Technology Acceptance Model for Empirically Testing New End-User Systems," MIS Quarterly, vol. 13, no. 3, pp. 319–340, 1989.
[6] R. Chand and S. Pandey, "Role of Institutional Intermediaries in Agri-Digital Adoption," Economic & Political Weekly, vol. 59, no. 18, pp. 41–49, 2024.
[7] USDA, AI and Remote Sensing for Yield Forecasting, Technical Bulletin, 2023.
[8] Ministry of Agriculture, Digital Agriculture Mission (2021–26), Government of India, New Delhi, 2022.
[9] IFAD, Institutional Pathways for AI Adoption in Smallholder Systems, Rome, 2023.
[10] NITI Aayog, Precision Agriculture Report, Government of India, 2023.
[11] ICRISAT, Village-Level Studies: AI and Resilience in Vidarbha, Hyderabad, 2022.
[12] NSSO, Household Technology Use in Rural India, Report No. 583, 2019.
[13] International Fund for Agricultural Development (IFAD), Digital Transformation and Institutional Pathways for Sustainable Agriculture, Rome, 2024.
[14] Ministry of Agriculture, Agricultural Census of India, 2022.
[15] A. Deshmukh, R. Patil, and S. Bhattacharya, "Determinants of Agri-Digital Adoption in Semi-Arid Regions of Maharashtra," Indian Journal of Agricultural Economics, vol. 78, no. 3, pp. 355–369, 2023.
[16] R. Chand and S. Pandey, "Institutional Intermediation in Agri-Digital Adoption," EPW, vol. 59, no. 18, pp. 41–49, 2024.
[17] OECD, Data Governance in Agriculture: Privacy and Ethics, Paris, 2024.
[18] R. Sharma and N. Devi, "Women and Digital Agriculture in India," Gender, Technology and Development, vol. 28, no. 2, pp. 109–127, 2024.
[19] A. Deshmukh et al., "Smart Irrigation in Semi-Arid Regions," Sustainability, vol. 15, no. 12, pp. 9921–9938, 2023.
[20] IFPRI, Nutrient Efficiency in Digital Agriculture, Washington DC, 2022.
[21] S. Bose et al., "Empirical Gaps in AI Impact Studies for Smallholders," EPW, vol. 59, no. 9, pp. 49–58, 2024.
[22] D. Barman, "Longitudinal Assessment of Sustainable Digital Agriculture," Sustainability, vol. 16, no. 3, pp. 1192–1205, 2024.
[23] P. Mishra, "Behavioral Insights into Agri-Digital Adoption," Journal of Rural Studies, vol. 102, pp. 155–168, 2023.