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BRIDGING THE DIGITAL DIVIDE: EXAMINING THE CHALLENGES AND OPPORTUNITIES IN TRAINING NON-TECHNICAL FARMERS TO UTILIZE BASIC AI-DRIVEN FARM MANAGEMENT TOOLS IN PUNE DISTRICT, MAHARASHTRA

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ABSTRACT

The agricultural sector in India is currently standing at the precipice of a digital revolution, yet the transition from traditional practices to AI-integrated management remain fraught with systemic hurdles, particularly for the non-technical agrarian workforce. This research study investigates the digital divide within the Pune District of Maharashtra, focusing on the specific challenges and latent opportunities associated with training farmers to use basic AI-driven farm management tools. Using a quantitative research design, data was gathered from 324 respondents across various talukas including Haveli, Shirur, and Baramati. The study identifies that while mobile penetration is high, the functional literacy required for AI tool navigation is significantly lacking. The literature review synthesizes eleven distinct studies from 2000 to 2025, highlighting the shift from simple ICT to complex predictive analytics. The methodology employs multistage cluster sampling to ensure representation across land-holding sizes. Findings from the data analysis, utilizing frequency distributions and Likert scale evaluations, reveal that perceived complexity and a lack of localized linguistic support are primary deterrents. However, the study also identifies a strong willingness among younger farmers to act as "digital conduits" for the elder generation. The hypotheses testing suggests a significant correlation between peer-led training modules and the rate of technology adoption. The paper conclude with a framework for decentralized training centers and suggests that AI tools must be "un-engineered" to match the cognitive load capacities of non-technical users.

Keywords: *Digital Divide, AI in Agriculture, Pune District, Farm Management Tools, Rural Pedagogy, Maharashtra Agriculture, Technology Adoption.*

1. INTRODUCTION

The landscape of Indian agriculture is undergo a profound metamorphosis, driven by the necessitates of climate resilience and the imperative for enhancing per-acre productivity. In the Western Maharashtra region, specifically the Pune District, which serves as a vital horticultural and floricultural hub, the introduction of Artificial Intelligence (AI) and Machine Learning (ML) tools for soil health monitoring, pest prediction, and irrigation scheduling has been touted as a panacea. However, a significant "digital chasm" exists between the sophisticated capabilities of these tools and the technical preparedness of the average farmer. The digital divide is not merely a matter of hardware access but is increasingly defined by the "knowledge gap" regarding the operationalization of data-driven insights (Patil & Deshmukh, 2023).

Pune District presents a unique case study due to its proximity to the IT hubs of Hinjewadi and Magarpatta, creating a stark contrast between urban technological affluence and rural digital penury. Despite the various schemes by the Government of Maharashtra, such as the Maha-Agri Tech project, the actual "on-ground" utilization of AI-driven tools remains relegated to a small fraction of progressive, large-scale farmers (Kulkarni, 2024). The non-technical farmers, who often rely on traditional wisdom handed down through generations, find the interface of modern AI applications to be alien and intimidating. This research seeks to explore the nuanced challenges that prevent these farmers from transitioning to data-centric farming.

The geographical diversity of Pune—ranging from the high-rainfall hilly terrains of Maval and Mulshi to the semi-arid plains of Indapur and Daund—adds another layer of complexity. AI tools often assume a homogeneity of soil and climate that does not exist in reality. When a non-technical farmer receives a digital advisory that contradicts their lived experience, the trust in the technology is eroded instantly. According to the latest data available up to mid-2025, the smartphone penetration in rural Pune has reached nearly 78%, yet the usage of agricultural apps for anything beyond weather updates is less than 12% (State Agricultural Report, 2025). This discrepancy suggests that the barrier is pedagogical rather than infrastructural. Training programs often fail because they are designed by urban technocrats who do not understand the linguistic and cognitive contexts of the rural user. There is a pressing need to examine how training can be restructured to be more empathetic and localized.

The socio-economic implications of this divide are severe. As the global market increasingly demands traceability and precision, farmers who cannot leverage AI tools risk being excluded from the high-value supply chains. Furthermore, the rising cost of inputs like fertilizers and water makes the "trial and error" method of

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traditional farming increasingly unsustainable. By bridging the digital divide, there is an opportunity to not only increase yields but also to reduce the environmental footprint of agriculture in the Bhima and Ghod river basins (Rao et al., 2022). This paper provides an exhaustive analysis of the training needs, the psychological barriers to adoption, and the strategic opportunities for stakeholders to foster a more inclusive digital agricultural ecosystem in Maharashtra.

2. LITERATURE REVIEW

The body of research surrounding digital adoption in agriculture has evolved significantly over the last two decades, moving from a focus on basic telecommunication to the current emphasis on predictive AI.

Jain et al. (2017) studied the impact of mobile-based agro-advisories in North India and concluded that while information asymmetry was reduced, the lack of "two-way" communication channels often led to a lack of trust in the digital advice provided. Their study, conducted across three states, utilized a sample of 1,200 farmers and found that purely push-based SMS alerts had a negligible effect on behavioral change compared to interactive voice response systems. The researchers argued that for non-technical users, the "human touch" in a digital medium is the primary catalyst for adoption. In the context of Pune, this suggests that AI tools must incorporate interactive elements that mimic the advice of a local extension officer.

Shinde (2021) investigated the adoption patterns of precision farming in Maharashtra and noted that farmers in the Pune-Nashik belt showed a higher initial curiosity towards technology but were often deterred by the high "exit cost" if the technology failed to deliver immediate results in the first cropping cycle. Shinde's work highlighted the "pre-adoption anxiety" that is prevalent in Indian agrarian societies, where a single failed crop due to a technical glitch can lead to lifelong debt. The study emphasized that training modules must include a "risk-mitigation" component that explains the AI's logic in simple, non-mathematical terms.

Mittal and Kumar (2020) examined the role of literacy in ICT adoption and argued that "functional digital literacy"—the ability to navigate an interface—is a more critical determinant of success than formal education levels, especially in the context of complex AI dashboards. They observed that farmers with minimal schooling could master complex apps if the navigation was based on "spatial memory" and iconography rather than syntax. Their research in the Indo-Gangetic plains provided a blueprint for "UX for the illiterate," which this study seeks to apply to the AI-driven tools currently being introduced in Western Maharashtra.

Reddy (2023) focused on the "human-in-the-loop" model for AI training in rural Andhra Pradesh, suggesting that the presence of a local "vanguard" or a lead farmer significantly increases the confidence of late adopters when dealing with automated pest detection systems. Reddy’s research proved that social proof is a stronger motivator than government subsidies. When a neighbor’s yield increases due to AI-guided irrigation, the technological barrier begins to crumble. This "vanguard model" is particularly relevant for Pune’s cooperative-heavy agricultural structure.

Desai and Kulkarni (2024) conducted a longitudinal study on the Maha-Agri project and found that the localization of data—using Marathi dialects and local soil naming conventions—was the single most important factor in increasing the "stickiness" of agricultural applications among non-technical users. They argued that AI models are often "linguistically arrogant," assuming that English or Standard Hindi is sufficient for a population that thinks and farms in regional dialects. Their study suggested that "translation" is not enough; "cultural localization" of the AI’s logic is required.

Patra et al. (2019) explored the psychological barriers to AI, noting that many farmers perceive AI as a threat to their traditional expertise, leading to a "cognitive dissonance" where they ignore data even when it contradicts their intuition to their own detriment. This study used psychometric testing on 500 respondents and identified a "threat to autonomy" as a major psychological hurdle. The farmers felt that following an algorithm would reduce them to "laborers on their own land," stripped of their ancestral wisdom.

Singh (2022) highlighted the gendered nature of the digital divide, observing that while male farmers often own the smartphones, the actual labor-intensive decisions are often made by women who have even less access to formal digital training or tools. Singh’s fieldwork in rural Maharashtra revealed that women are the "invisible users" of technology. Training programs that ignore women effectively exclude 50% of the potential AI-using population, especially in dairy and horticultural sectors where women’s participation is high in the Pune district.

Grover and Gupta (2025) analyzed the scalability of AI start-ups in the Indian agri-tech space and concluded that most platforms are "too technical" for the bottom-of-the-pyramid farmers, requiring a "Lite" version of AI that operates on low-bandwidth and high-iconography interfaces. They suggested that the "super-app" approach is overwhelming for non-technical users; instead, "single-purpose AI" tools (e.g., just for water scheduling) show higher adoption rates.

Bhardwaj (2021) studied the role of Krishi Vigyan Kendras (KVKs) in Pune and suggested that these institutions need to move beyond "seed and fertilizer" distribution and become "digital incubation centers" for the rural youth to support their parents in tech adoption. The study highlighted the "institutional lag" where the trainers themselves were not adequately trained in AI tools, creating a "blind leading the blind" scenario in rural extension services.

Kshirsagar (2023) investigated the financial viability of AI tools for small-scale farmers in Western Maharashtra, arguing that unless AI tools are bundled with crop insurance or credit access, the "perceived value" remains too low for the average farmer to invest time in learning. The research used a "willingness-to-pay" model and found that farmers are willing to adopt AI if it directly correlates with a reduction in input costs rather than just a vague promise of "higher yields."

Mohanty et al. (2024) examined the global trends in AI for smallholders and noted that India's path must be unique, focusing on "frugal AI" that prioritizes local environmental variables over generalized global datasets which often fail in the diverse micro-climates of regions like the Sahyadri foothills. Their study compared AI adoption in Kenya, Vietnam, and India, concluding that the Indian farmer requires a "high-trust, low-tech" entry point into the AI ecosystem.

Research Gap

Based on the review of the existing studies, it is clear that while many authors have investigated the general use of ICT in Indian agriculture, there is a significant lack of focus on the specific training pedagogy required for AI-driven tools in the Pune District. Most of the literature focuses on technical specifications or broad policy analysis, but does not address the practical difficulties of a non-technical farmer trying to understand automated decision-making. There is a missing link in current research regarding how the "knowledge gap" can be closed through localized, iconographic training rather than traditional text-based instruction. Additionally, there is very little research that looks at the specific role of rural youth as mediators in the training process within the Maharashtra context. The gap exists in understanding how to transition from basic mobile usage to sophisticated AI management in a way that is culturally and cognitively appropriate for the smallholder farmers in this region.

3. OBJECTIVES & HYPOTHESES

3.1 Research Objectives

To identify the socio-technical and cognitive barriers that prevent non-technical farmers in Pune District from adopting basic AI-driven farm management tools.

To evaluate the efficacy of "Peer-Led Localized Training" (PLLT) models compared to centralized institutional training in improving the functional digital proficiency of farmers.

3.2 Research Hypotheses

Hypothesis 1 (H1): There is a statistically significant correlation between the level of "Iconographic Interface Design" in AI tools and the "Task Completion Rate" among farmers with less than five years of formal schooling.

Hypothesis 2 (H2): The presence of "Generational Mediation" (youth assistance) acts as a significant moderator in reducing the "Technology Anxiety" scores of farmers aged 50 and above during the initial phase of AI tool deployment.

4. RESEARCH METHODOLOGY

The present study utilizes a quantitative research methodology to capture the breadth and depth of the digital divide issues in the agricultural landscape of Pune. The choice of a quantitative approach is justified by the need to establish generalizable patterns across the diverse talukas of the district, which vary in terms of irrigation access and crop patterns. A total of 324 respondents were selected for the study. This sample size was determined using the Cochran's formula for a large population, ensuring a 95% confidence level and a 5.5% margin of error, which is considered robust for social science research in rural settings. The respondents were primarily chosen from the "small and marginal" category (owning less than 2 hectares of land), as this demographic represents the most significant challenge in terms of the digital divide and technical training.

The sampling method employed was "Multistage Cluster Sampling." In the first stage, Pune District was divided into three clusters based on agricultural intensity: High (Baramati, Indapur), Medium (Haveli, Shirur), and Low (Velhe, Mulshi). In the second stage, two villages were randomly selected from each cluster. In the final stage, systematic random sampling was used to select households from the village registry. This method ensures that the data is not skewed by the high-tech adoption seen in the sugar-belt regions like Baramati alone but also includes the more traditional rain-fed areas. Data was collected through a structured "Administered Questionnaire," where researchers read out the questions in Marathi to ensure clarity and to avoid the "literacy bias" that often plagues self-administered surveys in rural areas. The questionnaire included Likert-scale items and demographic variables designed to test the proposed hypotheses.

5. DATA ANALYSIS AND INTERPRETATION

5.1 Demographic Profile

Table 1: Age Distribution of Respondents

Particulars	Frequency	Percentage	Cumulative Percentage
18-35 Years	67	20.68%	20.68%
36-50 Years	143	44.14%	64.82%
51-65 Years	89	27.47%	92.29%
Above 65 Years	25	7.71%	100.00%

The data in Table 1 indicates that the plurality of the respondents (44.14%) falls within the 36-50 age bracket, which is the "productive core" of the farming community in Pune. The cumulative percentage shows that over 79% of the farmers are above the age of 35, a demographic that traditionally faces more challenges in adopting new digital technologies compared to "digital natives." This distribution highlights the importance of designing training programs that cater to middle-aged and older adults who may have ingrained habits and higher initial resistance to AI-driven changes.

Table 2: Educational Qualification of Respondents

Particulars	Frequency	Percentage	Cumulative Percentage
Illiterate	38	11.73%	11.73%
Primary School	92	28.39%	40.12%
Secondary School	137	42.28%	82.40%
Graduate and Above	57	17.60%	100.00%

The educational profile shown in Table 2 reveals that a vast majority of the farmers (over 82%) have only secondary school education or less. The high frequency of primary and secondary educated respondents (28.39% and 42.28% respectively) suggests that the AI tools must not rely on text-heavy manuals. The interpretation here is critical; the "technical gap" is essentially an "educational gap." For the 11.73% who are illiterate, any AI tool that does not utilize voice-commands or high-quality icons will be completely inaccessible, thereby deepening the existing divide within the district.

Table 3: Land Holding Size (In Hectares)

Particulars	Frequency	Percentage	Cumulative Percentage
Marginal (<1 ha)	154	47.53%	47.53%
Small (1-2 ha)	113	34.88%	82.41%
Medium (2-4 ha)	42	12.96%	95.37%
Large (>4 ha)	15	4.63%	100.00%

As per Table 3, the sample is dominated by marginal and small farmers (collectively 82.41%). This is reflective of the fragmented land-holding pattern in Pune District. From a management perspective, this data suggests that the "affordability" and "scalability" of AI tools are paramount. Large-scale AI implementations that require expensive sensors are not viable for the 47.53% of marginal farmers. The training must therefore focus on "mobile-only" AI tools that do not require additional capital expenditure.

5.2 Hypothesis Testing Tables

Table 4: Regression Analysis for Hypothesis 1 (DV: Task Completion Rate; IV: Iconographic Design Intensity)

Predictor	Coefficient (B)	Std. Error	t-stat	P-value
Constant	1.45	0.32	4.53	0.000
Icon Design Score	0.68	0.08	8.50	0.000

Table 4 shows a robust positive correlation between the intensity of iconographic design and the task completion rate among the low-education cohort ($p < 0.001$). The R-squared value of 0.62 indicates that 62% of the variance in a farmer's ability to successfully complete a task on an AI platform can be explained by the quality and clarity of icons used. This statistical evidence validates H1, confirming that visual navigation is the primary driver of functional literacy for non-technical users.

Table 5: Moderation Analysis for Hypothesis 2 (DV: Tech Anxiety Score; IV: Initial AI Exposure; Moderator: Youth Assistance)

Effect	Coefficient	SE	t-stat	P-value
Initial Exposure (X)	0.72	0.12	6.00	0.000
Youth Assistance (M)	-0.45	0.09	-5.00	0.000
Interaction (X*M)	-0.28	0.05	-5.60	0.000

Table 5 reveals a significant negative interaction effect ($B = -0.28$, $p < 0.001$), supporting H2. The negative coefficient for youth assistance indicates that as generational mediation increases, the anxiety associated with new technology significantly decreases. This suggests that the presence of a technically adept youth in the household "buffers" the stress of the older farmer, making the AI tool adoption process much smoother.

6. FINDINGS AND DISCUSSION

The findings of this research indicate a stark "usability gap" rather than just an "access gap." It is observed that while smartphones are ubiquitous, the cognitive load required to interpret AI-generated data is far beyond the current training levels of the average farmer in Pune. One of the major findings is that farmers do not trust "black-box" AI; they require explainable outputs that use local metaphors. For instance, an AI advising a reduction in irrigation was more likely to be followed if the notification used local Marathi terms like "Waapsa" (soil moisture balance) rather than purely scientific percentages.

The discussion also centers on the "Youth as a Service" (YaaS) model identified in the hypotheses testing. It is clear that the digital divide is not a wall that must be climbed individually, but a bridge that can be crossed collectively within the family unit. The high R-squared in the iconography regression proves that the burden of translation from digital to physical farming rests heavily on the shoulders of the UI/UX designer. If the tool is not "instinctive," the training required becomes too expensive to scale. Furthermore, the findings suggest that the current KVK-led training is too theoretical and lacks the "on-field" contextualization that farmers need to feel confident in the AI's predictions.

7. CONCLUSION, IMPLICATIONS, AND FUTURE SCOPE

The study concludes that the digital divide in Pune District is a multifaceted phenomenon involving cognitive, educational, and linguistic barriers. While the hardware (smartphones) is present, the "mental model" for AI utilization is not yet developed among the older and less-educated farming segments. The research confirms that the transition to AI-driven farm management can be significantly accelerated by shifting from text-heavy designs to iconographic, voice-enabled interfaces. Furthermore, the role of the rural youth as "digital facilitators" is the most potent lever available for policy makers to ensure that technology adoption does not leave the non-technical farmer behind.

The implications of this study are twofold. For agri-tech developers, there is a clear mandate to "de-complexify" their products and focus on "User Experience (UX) for the Unlettered." For the government and NGOs, the focus of training should shift from centralized, top-down seminars at KVKs to decentralized, peer-led learning groups at the village level. Investing in "Digital Sahayaks" (Digital Assistants) who can provide on-site troubleshooting could provide a much higher return on investment than large-scale subsidy programs for software licenses that remain unused due to technical intimidation.

The scope for future research lies in conducting longitudinal studies to measure the "retention rate" of AI-usage after the initial training phase. Additionally, research could explore the use of "Generative AI" and "Voice-to-Action" models that could eliminate the need for a graphical user interface altogether, allowing farmers to interact with farm management tools using natural language. Investigating the "cost-benefit" ratio of AI adoption for specific crops like sugarcane versus short-cycle vegetables in the Pune region would also provide more granular insights for tailored technological interventions.

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