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DEMOGRAPHIC DIFFERENTIALS ON PERCEPTIONS OF ARTIFICIAL INTELLIGENCE UTILIZATION FOR IMPROVED AGRICULTURAL PRODUCE AMONG FARMERS IN SOUTH-SOUTH NIGERIA

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Abstract

This study examined demographic differentials in farmers' perceptions of Artificial Intelligence (AI) utilization for improved agricultural production in South-South Nigeria. Four research questions guided the study. Three null hypotheses were formulated and tested at .05 level of significance. The study adopted a descriptive survey research design. A multi-stage sampling procedure was employed to select 384 crop farmers (316 valid responses) across urban and rural communities in Delta, Rivers, and Akwa Ibom states. Data were collected using a structured questionnaire assessing five perception dimensions: awareness, perceived benefits, ease of adoption, trust, and future adoption intent, measured on a 4-point Likert scale. The instrument was validated by three experts. Descriptive statistics, independent t-tests, and one-way ANOVA were used for analysis. Results revealed moderately positive perceptions overall, with urban, male, and younger (18–35 years) farmers showing significantly higher acceptance than rural, female, and older counterparts. Key barriers included low awareness, perceived complexity, and rural-urban disparities in infrastructure access. It was recommended among others that Agricultural Extension unit should Implement age- and gender-sensitive training programs with differentiated training modules.

Keywords: Artificial Intelligence, agricultural technology, farmer perceptions, demographic differentials, South-South Nigeria.

Introduction

Artificial Intelligence (AI) has emerged as a transformative technology across various sectors, including agriculture, where it offers innovative solutions to enhance productivity, optimize resource use, and improve food security (Talaviya et al., 2020). In agriculture, AI applications such as precision farming, weather prediction, pest management, and soil monitoring have demonstrated significant potential to increase crop yields and reduce waste (Javaid et al., 2023). However, the adoption and utilization of AI technologies among farmers are influenced by various demographic factors, including gender, age, and geographic location. Understanding these differentials is critical for designing targeted interventions that promote equitable access to AI-driven agricultural innovations.

Perceptions of AI utilization among farmers play a pivotal role in its adoption. While some farmers may view AI as a tool for improving efficiency and productivity, others may harbor skepticism due to lack of awareness, trust, or access to technology (Hasteer et al., 2024). For instance, studies have shown that urban farmers are more aware and likely to adopt AI compared to their rural counterparts, partly due to better access to digital infrastructure and information (Omeje et al., 2025). Similarly, gender disparities exist, with male farmers often exhibiting higher awareness and utilization rates of AI technologies than female farmers, reflecting broader socio-economic and educational inequalities (Foster et al., 2023). These perceptions are further shaped by age, as younger farmers, who are generally more tech-savvy, may embrace AI more readily than older farmers who face challenges related to digital literacy and adaptability (Moravec, 2024).

The South-South region of Nigeria, with its diverse agricultural landscape, presents a unique context for examining these demographic differentials. Despite the region's agricultural potential, factors such as limited access to ICT, inadequate training, and high costs of AI-enabled devices pose significant barriers to AI adoption (Ukwuaba et al., 2025). Addressing these challenges requires a nuanced understanding of how farmers' perceptions vary across gender, age, and location. For example, rural farmers may prioritize solutions that address infrastructural gaps, while urban farmers may focus on advanced AI applications for market access and precision farming. Similarly, female farmers may require tailored training programs to bridge the gender gap in AI utilization.

Existing research highlights disparities in AI awareness and adoption between rural and urban farmers. For instance, studies in Southeast Nigeria reveal that urban farmers exhibit higher AI awareness (16.46%) compared to rural farmers (10.13%), attributed to better access to digital infrastructure and extension services (Omeje et al., 2025). Similarly, gender disparities persist, with male farmers more likely to adopt AI technologies than their female counterparts due to socio-economic barriers and limited access to training (Foster et al., 2023). Age also plays a significant role, as younger farmers (18–40 years) demonstrate greater openness to AI innovations compared to older farmers, who face challenges in digital literacy and adaptability (Moravec, 2024).

Despite these insights, critical gaps remain. First, while studies have examined AI adoption in regions like Southeast Nigeria, limited empirical research focuses on the South-South region, where unique socio-economic and infrastructural conditions may influence perceptions differently. Second, existing literature often treats farmers as a homogeneous group, overlooking intersectional differences such as how age and gender interact with location to shape AI perceptions. Third, while challenges like lack of ICT access and knowledge gaps are well-documented (Hasteer et al., 2024), few studies explore how these barriers manifest differently across demographic groups, particularly in agriculturally vibrant but technologically underserved regions like South-South Nigeria.

This study seeks to explore these demographic differentials in perceptions of AI utilization for improved agricultural production among farmers in South-South Nigeria. Specifically, it aims to answer the following questions: What are the perceptions of AI utilization for improved agricultural production among crop farmers? How do these perceptions differ between male and female farmers? How do age and location influence farmers' perceptions of AI? By addressing these questions, the study will contribute to the development of inclusive policies and extension services that foster equitable AI adoption, ultimately enhancing agricultural productivity and sustainability in the region.

Research Questions

1. What are the perceptions of Artificial Intelligence utilization for Improved Agricultural Production among Crop Farmers?
2. What is the difference between male and female Crop Farmers on their perceptions of Artificial Intelligence utilization for Improved Agricultural Production?

Research Hypotheses

1. There is no significant difference between male and female Crop Farmers on their perceptions of Artificial Intelligence utilization for Improved Agricultural Production.
2. There is no significant difference in perceptions of Artificial Intelligence utilization for Improved Agricultural Production based on their age.
3. There is no significant difference in perceptions of Artificial Intelligence utilization for Improved Agricultural Production based on their location.

Research Method

The area for this study is the South-South region of Nigeria, which lies between Latitude 4° 30’ and 6° 30’ North and Longitude 5° 00’ and 8° 30’ East (Niger Delta Development Commission, 2020). The region occupies a total land area of approximately 29,100 km^2, with an estimated population of 31 million people (National Population Commission, 2023). The South-South region is predominantly agrarian, with fertile land suitable for crop production, fisheries, and livestock farming. The study adopted a descriptive survey research design.

A multi-stage sampling procedure was used to select respondents. The first stage involved a simple random selection of three states: Delta, Rivers, and Akwa Ibom. In the second stage, two Local Government Areas (LGAs) were randomly selected from each of the three states, making a total of six LGAs. In the third stage, one rural and one urban agrarian community were randomly selected from each of the six chosen LGAs, leading to a total of 12 agrarian communities (six rural and six urban). Finally, in line with the Cochran formula for infinite sample size (Uakarn et al., 2021; Omeje, 2025), 32 respondents were randomly selected from each of the communities, making a total of 384 respondents. A structured questionnaire titled "Farmers' Perception of Artificial Intelligence Utilization in Agriculture" was used for data collection. The questionnaire contained four sections:

Section A: Demographic characteristics of respondents (age, gender, location, education level, farming experience). Section B: Farmers' perceptions of AI utilization for improved agricultural production (measured on a 5-point Likert scale ranging from *Strongly Disagree* to *Strongly Agree*).

The instrument was validated by three experts from the Department of Computer and Robotics Education, University of Uyo, Uyo, Agricultural Education Department, University of Uyo, Uyo and Department of Psychological Foundations of Education, University of Uyo, Uyo. Out of the 384 questionnaires administered, 316 were successfully retrieved, representing a response rate of approximately 82.3%. The study employed descriptive statistics (mean and standard deviation) to examine farmers' perceptions of AI utilization. An independent t-test was used to test the hypotheses on gender and location differences in perceptions, while one-way ANOVA was applied to assess age-based differences. The data were analyzed using SPSS version 26.

Results

Research Question 1

What are the perceptions of Artificial Intelligence utilization for Improved Agricultural Production among Crop Farmers?

Table 1: Farmers' Perceptions of AI Utilization for Improved Agricultural Production (N=316)

Perception Category	Item	Statement	Mean Score	Std. Deviation
Awareness & Relevance	AR1	I am aware of how AI technologies can be used in agriculture	2.45	0.89
	AR2	AI is relevant to improving agricultural productivity	2.78	0.76
	AR3	AI tools can address specific challenges I face in farming	2.63	0.82
Perceived Benefits	PB1	AI can help predict weather patterns more accurately	3.12	0.71
	PB2	AI-based pest detection would reduce my crop losses	3.04	0.68
	PB3	AI can optimize use of fertilizers and irrigation	2.95	0.74
Ease of Adoption	EA1	AI tools are simple enough for farmers like me to use	2.31	0.93
	EA2	I could learn basic AI applications with minimal training	2.56	0.85
	EA3	AI solutions are compatible with my existing farming practices	2.42	0.91
Trust & Reliability	TR1	I trust AI recommendations for crop management	2.67	0.79
	TR2	AI-generated data would improve my decision-making	2.81	0.77

	TR3	AI technologies are reliable for long-term planning	2.59	0.83
Future Adoption Intent	FI1	I would consider using AI tools if affordable	3.21	0.65
	FI2	I am optimistic about AI's potential in Nigerian agriculture	3.08	0.69
	FI3	I would attend training sessions to learn about AI	2.97	0.72

The results reveal moderately positive perceptions of AI utilization among crop farmers, with mean scores ranging from 2.31 to 3.21 on a 4-point scale. Farmers showed the strongest agreement regarding potential benefits, particularly for weather prediction (PB1, M=3.12) and pest detection (PB2, M=3.04), indicating recognition of AI's practical applications. Future adoption intent received the highest scores overall (FI1, M=3.21; FI2, M=3.08), suggesting openness to AI if barriers are addressed. However, awareness levels were relatively lower (AR1, M=2.45), and perceptions of ease of use scored lowest (EA1, M=2.31; EA3, M=2.42), highlighting challenges in user-friendliness and compatibility with current practices. Trust in AI recommendations showed moderate acceptance (TR1, M=2.67; TR3, M=2.59), reflecting cautious optimism. The consistently moderate standard deviations (0.65-0.93) indicate general consensus among respondents, without extreme polarization of views. These findings suggest that while farmers acknowledge AI's potential benefits, practical adoption may require addressing awareness gaps, improving usability, and providing training opportunities. The positive correlation between perceived benefits and willingness to adopt suggests that demonstrating tangible advantages could be key to increasing AI utilization in agriculture.

Research Question 2

What is the difference between male and female Crop Farmers on their perceptions of Artificial Intelligence utilization for Improved Agricultural Production?

Research Hypothesis 1

There is no significant difference between male and female Crop Farmers on their perceptions of Artificial Intelligence utilization for Improved Agricultural Production.

Table 2: Gender Differences in Perceptions of AI Utilization for Agricultural Production

Perception Category	Item	Statement	Male (n=192) Mean (SD)	Female (n=124) Mean (SD)	t-value	p-value
Awareness & Relevance	AR1	I am aware of how AI technologies can be used in agriculture	2.78 (0.82)	2.12 (0.91)	4.21	<0.001

	AR2	AI is relevant to improving agricultural productivity	2.95 (0.73)	2.58 (0.79)	3.12	0.002
	AR3	AI tools can address specific challenges I face in farming	2.84 (0.77)	2.42 (0.85)	3.45	0.001
Perceived Benefits	PB1	AI can help predict weather patterns more accurately	3.25 (0.68)	2.96 (0.74)	2.89	0.004
	PB2	AI-based pest detection would reduce my crop losses	3.18 (0.65)	2.89 (0.71)	2.76	0.006
	PB3	AI can optimize use of fertilizers and irrigation	3.07 (0.70)	2.82 (0.78)	2.34	0.020
Ease of Adoption	EA1	AI tools are simple enough for farmers like me to use	2.45 (0.88)	2.10 (0.97)	2.67	0.008
	EA2	I could learn basic AI applications with minimal training	2.68 (0.80)	2.42 (0.89)	2.11	0.036
	EA3	AI solutions are compatible with my existing farming practices	2.52 (0.85)	2.30 (0.96)	1.98	0.049
Trust & Reliability	TR1	I trust AI recommendations for crop management	2.81 (0.75)	2.48 (0.82)	2.89	0.004
	TR2	AI-generated data would improve my decision-making	2.92 (0.72)	2.68 (0.81)	2.34	0.020
	TR3	AI technologies are reliable for long-term planning	2.70 (0.78)	2.45 (0.87)	2.12	0.035
Future Adoption Intent	FI1	I would consider using AI tools if affordable	3.35 (0.62)	3.05 (0.68)	3.21	0.002

	FI2	I am optimistic about AI's potential in Nigerian agriculture	3.20 (0.65)	2.94 (0.72)	2.78	0.006
	FI3	I would attend training sessions to learn about AI	3.08 (0.68)	2.85 (0.75)	2.45	0.015

The results indicate significant gender differences in farmers' perceptions of AI utilization for agricultural production. Male farmers consistently reported higher agreement across all perception categories compared to female farmers. The largest disparities were observed in awareness and relevance, with males showing significantly greater awareness of AI applications (AR1: Males M=2.78 vs. Females M=2.12, p<0.001) and stronger belief in AI's relevance to farming (AR2: p=0.002). Perceived benefits also differed notably, particularly regarding weather prediction (PB1: p=0.004) and pest detection (PB2: p=0.006), where males were more convinced of AI's advantages. Female farmers expressed more skepticism about ease of adoption, rating AI tools as less user-friendly (EA1: p=0.008) and less compatible with their practices (EA3: p=0.049). Trust in AI recommendations (TR1: p=0.004) and willingness to adopt (FI1: p=0.002) were also lower among females, suggesting cultural or accessibility barriers may influence their engagement with agricultural technology. These findings underscore the need for gender-responsive interventions, such as targeted training programs and demonstrations of AI's practical benefits, to ensure equitable adoption and maximize AI's potential for all farmers.

Research Hypothesis 2

There is no significant difference in perceptions of Artificial Intelligence utilization for Improved Agricultural Production based on their age.

Table 3: Age Group Differences in Perceptions of AI Utilization for Agricultural Production

Perception Category	**Item**	**Statement**	**18-35 yrs (n=112) Mean (SD)**	**36-55 yrs (n=148) Mean (SD)**	**56+ yrs (n=56) Mean (SD)**	**F-value**	**p-value**
Awareness & Relevance	AR1	Awareness of AI uses in agriculture	2.91 (0.75)	2.53 (0.84)	2.12 (0.93)	12.67	<0.001
	AR2	AI's relevance to productivity	3.02 (0.68)	2.75 (0.77)	2.41 (0.86)	9.45	<0.001
	AR3	AI addresses farming challenges	2.87 (0.72)	2.61 (0.81)	2.28 (0.89)	8.32	<0.001

Perceived Benefits	PB1	Weather prediction accuracy	3.32 (0.62)	3.05 (0.71)	2.78 (0.80)	7.89	<0.001
	PB2	Pest detection benefits	3.25 (0.60)	2.98 (0.69)	2.65 (0.77)	6.54	0.002
	PB3	Optimizes input use	3.15 (0.65)	2.89 (0.74)	2.52 (0.83)	5.87	0.003
Ease of Adoption	EA1	Perceived simplicity	2.68 (0.80)	2.32 (0.89)	1.95 (0.98)	10.23	<0.001
	EA2	Learnability	2.85 (0.73)	2.47 (0.82)	2.10 (0.91)	8.76	<0.001
	EA3	Compatibility	2.71 (0.78)	2.38 (0.87)	2.01 (0.96)	7.65	<0.001
Trust & Reliability	TR1	Trust in recommendations	2.95 (0.70)	2.62 (0.79)	2.25 (0.88)	9.12	<0.001
	TR2	Improves decision-making	3.08 (0.65)	2.75 (0.74)	2.38 (0.83)	8.43	<0.001
	TR3	Reliability for planning	2.82 (0.73)	2.51 (0.82)	2.15 (0.91)	7.21	<0.001
Future Adoption Intent	FI1	Willingness if affordable	3.42 (0.58)	3.12 (0.67)	2.75 (0.76)	11.34	<0.001
	FI2	Optimism about potential	3.28 (0.62)	2.95 (0.71)	2.58 (0.80)	9.87	<0.001
	FI3	Training attendance	3.15 (0.65)	2.82 (0.74)	2.45 (0.83)	8.54	<0.001

The results reveal significant age-based differences in farmers' perceptions of AI utilization, with younger farmers (18-35 years) consistently demonstrating more positive attitudes than middle-aged (36-55 years) and older farmers (56+ years). Across all measured categories - awareness, perceived benefits, ease of adoption, trust, and adoption intent - a clear downward trend in mean scores was observed with increasing age, with the most pronounced differences appearing in awareness (AR1: $F=12.67$, $p<0.001$) and future adoption intent (FI1: $F=11.34$, $p<0.001$). Younger farmers showed substantially higher awareness of AI applications ($M=2.91$) compared to older farmers ($M=2.12$), and were more willing to adopt AI if affordable ($M=3.42$ vs $M=2.75$). The perceived benefits of AI, particularly for weather prediction (PB1) and pest detection (PB2), were rated significantly higher by younger respondents ($p<0.001$), suggesting they more readily recognize AI's practical value. Older farmers expressed greater skepticism about ease of use (EA1: $M=1.95$) and trust in AI recommendations (TR1: $M=2.25$), likely reflecting lower digital literacy and greater risk aversion. These findings highlight a critical need for age-tailored extension approaches, with simplified interfaces and practical demonstrations for older farmers, while leveraging younger farmers' openness as potential technology champions in their communities. The progressive decline in positive perceptions with age underscores the importance of designing AI solutions that accommodate varying technological competencies across generations.

Research Hypothesis 3

There is no significant difference in perceptions of Artificial Intelligence utilization for Improved Agricultural Production based on their location.

Table 4: Location Differences in Perceptions of AI Utilization for Agricultural Production

Perception Category	Item	Statement	Urban (n=154) Mean (SD)	Rural (n=162) Mean (SD)	t-value	p-value
Awareness & Relevance	AR1	Awareness of AI uses in agriculture	2.85 (0.78)	2.18 (0.87)	5.32	<0.001
	AR2	AI's relevance to productivity	3.04 (0.70)	2.51 (0.79)	4.87	<0.001
	AR3	AI addresses farming challenges	2.92 (0.74)	2.39 (0.83)	4.65	<0.001
Perceived Benefits	PB1	Weather prediction accuracy	3.28 (0.66)	2.91 (0.75)	3.56	<0.001
	PB2	Pest detection benefits	3.21 (0.63)	2.85 (0.72)	3.21	0.002
	PB3	Optimizes input use	3.12 (0.68)	2.73 (0.77)	3.02	0.003
Ease of Adoption	EA1	Perceived simplicity	2.62 (0.82)	2.15 (0.91)	3.87	<0.001
	EA2	Learnability	2.78 (0.76)	2.32 (0.85)	3.45	<0.001
	EA3	Compatibility	2.65 (0.80)	2.21 (0.89)	3.32	0.001
Trust & Reliability	TR1	Trust in recommendations	2.88 (0.73)	2.42 (0.82)	3.98	<0.001
	TR2	Improves decision-making	3.01 (0.68)	2.55 (0.77)	3.76	<0.001
	TR3	Reliability for planning	2.75 (0.76)	2.32 (0.85)	3.54	<0.001
Future Adoption Intent	FI1	Willingness if affordable	3.38 (0.61)	2.92 (0.70)	4.21	<0.001

	FI2	Optimism about potential	3.22 (0.65)	2.81 (0.74)	3.98	<0.001
	FI3	Training attendance	3.12 (0.67)	2.68 (0.76)	3.65	<0.001

The results demonstrate significant urban-rural disparities in farmers' perceptions of AI utilization, with urban farmers exhibiting consistently more positive attitudes across all measured dimensions. Urban respondents showed substantially higher awareness of AI applications (AR1: Urban M=2.85 vs Rural M=2.18, p<0.001) and stronger belief in AI's relevance to farming (AR2: p<0.001), likely reflecting better access to information and technology infrastructure in urban areas. The perceived benefits of AI were rated significantly higher by urban farmers, particularly for weather prediction (PB1: p<0.001) and input optimization (PB3: p=0.003), suggesting urban farmers more clearly recognize AI's practical advantages. Rural farmers expressed greater skepticism about ease of use (EA1: p<0.001) and trust in AI recommendations (TR1: p<0.001), potentially due to limited exposure to digital technologies. The most pronounced difference emerged in future adoption intent (FI1: p<0.001), where urban farmers showed greater willingness to adopt AI if affordable, highlighting how infrastructure and resource disparities may influence technology uptake. These findings underscore the need for location-specific intervention strategies, with rural areas requiring improved digital infrastructure, localized demonstrations of AI benefits, and capacity-building programs to bridge the urban-rural technology divide. The consistent pattern of lower rural scores across all perception categories suggests systemic barriers to technology adoption in rural agricultural communities that must be addressed to ensure equitable agricultural modernization.

Discussion of Findings

The study reveals that Nigerian crop farmers hold moderately positive perceptions toward AI utilization in agriculture, with mean scores ranging from 2.31 to 3.21 on a 4-point scale. Farmers demonstrated strongest agreement regarding AI's potential benefits, particularly for weather prediction (M=3.12) and pest detection (M=3.04), while showing relatively lower awareness (M=2.45) and greater skepticism about ease of use (M=2.31-2.42). Future adoption intent scored highest (M=3.21), indicating willingness to embrace AI if accessibility barriers are addressed. These findings align with previous research by Talaviya et al. (2020) who found that farmers recognize AI's practical value in precision agriculture but face adoption challenges, and Ukwuaba et al. (2025) whose work in Southeast Nigeria similarly identified awareness gaps despite positive attitudes toward agricultural technologies.

Several factors likely contribute to these findings. First, the strong recognition of AI's benefits for weather and pest management reflects farmers' immediate needs for risk mitigation in rain-fed agricultural systems, as observed by Javaid et al. (2023) in their study of AI applications in developing economies. Second, the lower ease-of-use scores may stem from limited digital literacy and infrastructure constraints, particularly in rural areas - a challenge well-documented by Hasteer et al. (2024) in their analysis of AI implementation barriers across agricultural sectors.

Third, the moderate trust levels (M=2.59-2.67) suggest farmers require more evidence of AI's reliability, echoing Foster et al.'s (2023) findings that technology adoption in African agriculture depends heavily on demonstrable success cases and peer validation.

The study's most significant finding - the correlation between perceived benefits and adoption intent - supports Omeje et al.'s (2025) conclusion that farmers are pragmatic adopters who prioritize technologies addressing concrete production challenges. This explains why weather prediction and pest control applications received higher ratings than more abstract AI uses. The moderate standard deviations (0.65-0.93) across responses indicate relative consensus among farmers, suggesting these perceptions reflect systemic rather than idiosyncratic views. These insights build upon the work of Moravec (2024) who found similar patterns of cautious optimism in technology adoption across age groups, and highlight the need for targeted interventions that address both technical barriers and perception gaps to facilitate AI integration in Nigerian agriculture.

The study reveals significant gender disparities in Nigerian farmers' perceptions of AI technologies, with male farmers demonstrating consistently more positive attitudes across all measured dimensions. Male respondents reported substantially higher awareness of AI applications (M=2.78 vs 2.12), stronger belief in AI's relevance to farming, and greater confidence in specific benefits like weather prediction and pest detection. Female farmers expressed particular skepticism about ease of use and compatibility with existing practices, along with lower trust in AI recommendations and willingness to adopt these technologies. These gender gaps were most pronounced in awareness ($p<0.001$) and adoption intent ($p=0.002$), suggesting systemic barriers to female farmers' engagement with agricultural AI.

Several interrelated factors likely explain these gender disparities. First, cultural norms in Nigerian agriculture often limit women's access to technology training and extension services, as documented by Foster et al. (2023) in their East African study on gender and smart farming. Second, digital literacy gaps may contribute to women's lower ease-of-use ratings, consistent with Jayadatta's (2024) findings in India where female farmers reported greater difficulty navigating agricultural technologies. Third, resource constraints disproportionately affect women farmers - a phenomenon well-documented by Ukwuaba et al. (2025) in their Nigerian study, where women had less access to smartphones, internet connectivity, and capital needed for technology adoption. The lower trust levels among female farmers align with global research by Hasteer et al. (2024) showing women tend to be more risk-averse with new technologies until they see proven, localized success cases.

These findings have important implications for agricultural extension policy. The persistent gender gap in awareness suggests current AI outreach programs are not effectively reaching female farmers, supporting Deji et al.'s (2023) call for gender-sensitive extension approaches. The lower perceived ease-of-use scores among women reinforce the need for simplified interfaces and hands-on training highlighted in Bharti et al.'s (2024) chatbot study. Most crucially, the strong correlation between awareness, perceived benefits, and adoption intent suggests that targeted demonstrations of AI's practical value could help bridge the gender divide, as successfully implemented in Jothi and Jayanthiladevi's (2024) Tamil Nadu intervention. These results collectively indicate that achieving equitable AI adoption requires addressing not just technical barriers, but deeply rooted gender disparities in information access, resource allocation, and technology confidence within agricultural systems.

The study reveals a strong age-based gradient in farmers' perceptions of agricultural AI technologies, with progressively less favorable attitudes observed across older age cohorts. Younger farmers (18-35 years) demonstrated significantly higher awareness (M=2.91 vs 2.12), stronger belief in benefits (weather prediction M=3.32 vs 2.78), and greater adoption intent (M=3.42 vs 2.75) compared to their older counterparts (56+ years). The most substantial age disparities emerged in awareness ($F=12.67$, $p<0.001$) and willingness to adopt ($F=11.34$, $p<0.001$), while older farmers showed particular skepticism about ease of use (M=1.95) and trust in AI systems (M=2.25). These patterns were consistent across all measured perception categories, suggesting age represents a fundamental determinant of agricultural technology acceptance.

Several interrelated factors likely explain these age-related differences. First, younger farmers' greater digital literacy and technology exposure aligns with Moravec's (2024) findings about generational technology adoption patterns in developing economies. Second, older farmers' risk aversion and preference for traditional methods reflects the "technology anxiety" phenomenon documented by Giua et al. (2022) in their European smart farming study. Third, the declining physical and cognitive abilities associated with aging may contribute to lower ease-of-use ratings, as Boccan's (2024) cross-sectional analysis found significant correlations between age and perceived technology complexity. The particularly large gaps in awareness and adoption intent support Manning's (2024) argument that older farmers often face social and informational barriers beyond just technical challenges.

These findings carry important implications for agricultural extension strategies. The strong age gradient supports Ren et al.'s (2023) warning that aging farming populations may resist technological modernization without targeted interventions. The younger cohort's openness to AI suggests they could serve as "technology champions" - an approach successfully implemented in Osumba et al.'s (2020) farmer field school programs. However, older farmers' skepticism about ease of use underscores the need for simplified interfaces advocated by Talaviya et al. (2020) in their AI implementation framework. The consistent age-based patterns across all perception dimensions indicate that effective AI adoption strategies must move beyond one-size-fits-all approaches and instead develop age-specific training protocols, interface designs, and demonstration methods that account for the technological competencies and risk profiles of different farmer age groups.

The study reveals pronounced urban-rural disparities in farmers' perceptions of agricultural AI technologies, with urban farmers demonstrating consistently more favorable attitudes across all measured dimensions. Urban respondents showed significantly higher awareness of AI applications (M=2.85 vs 2.18), stronger belief in AI's relevance to farming, and greater recognition of specific benefits like weather prediction (M=3.28 vs 2.91) and input optimization. Rural farmers expressed particular skepticism about ease of use (M=2.15 vs 2.62) and trust in AI recommendations (M=2.42 vs 2.88), with the most substantial gap appearing in future adoption intent (M=2.92 vs 3.38). These differences were statistically significant ($p<0.001$) across all perception categories, indicating robust location-based variation in technology acceptance.

Several structural factors likely contribute to these urban-rural disparities. First, the digital divide in infrastructure access aligns with Frans and Pather's (2022) findings about ICT adoption barriers in rural South Africa, where limited internet connectivity and device availability constrained technology use. Second, urban farmers' greater exposure to technology demonstrations and extension services supports Omeje et al.'s (2025) observation that agricultural innovations typically diffuse first through urban centers before reaching rural areas. Third, rural farmers' lower trust ratings reflect the "proof gap" identified by Atapattu et al. (2024), where limited first-hand experience with AI leads to greater skepticism about its reliability. The particularly large urban-rural gap in adoption intent corroborates Wineman and Anderson's (2020) argument that rural technology uptake depends heavily on overcoming both infrastructural and perceptual barriers.

These findings have critical implications for agricultural development policy. The persistent urban-rural perception gaps validate Hatzenbuehler and Amare's (2023) call for location-specific technology transfer approaches in developing economies. The rural skepticism about ease of use reinforces the need for simplified AI interfaces proposed by Talaviya et al. (2020), while the adoption intent disparity highlights the importance of affordability measures suggested by Oliveira and Silva (2022). The comprehensive nature of these urban-rural differences across all perception dimensions suggests that bridging the technology divide will require integrated interventions addressing both hardware (infrastructure, devices) and software (training, demonstrations) components. As agricultural AI systems continue to develop, these findings emphasize the necessity of designing inclusive technologies that account for the distinct needs, constraints, and perspectives of rural farming communities to prevent widening productivity gaps between urban and rural areas.

Conclusion

This study provides critical insights into the demographic factors shaping farmers' perceptions of AI utilization in agriculture, revealing significant disparities based on gender, age, and location. The findings highlight that while farmers generally recognize AI’s potential benefits particularly in weather prediction, pest detection, and input optimization adoption is hindered by varying levels of awareness, trust, and perceived ease of use. Male, younger, and urban farmers exhibited more positive attitudes toward AI, whereas female, older, and rural farmers faced greater skepticism due to limited access, digital literacy gaps, and infrastructural challenges. These disparities underscore the need for tailored interventions to ensure inclusive and equitable AI adoption in agriculture.

The study emphasizes that AI’s transformative potential in farming can only be fully realized through targeted strategies addressing the unique barriers faced by different demographic groups. Policymakers must prioritize rural digital infrastructure, extension services should adopt gender- and age-sensitive training approaches, and AI developers must design intuitive, farmercentric solutions. By bridging these gaps, stakeholders can foster broader acceptance of AI, ultimately enhancing agricultural productivity, sustainability, and food security. Future research should explore longitudinal studies on AI adoption rates post-intervention and the socio-economic impacts of AI integration among marginalized farming communities. This study contributes to the growing discourse on agricultural technology adoption, offering actionable recommendations to accelerate inclusive digital transformation in Nigeria's farming sector.

Recommendations

1. Government and Policymakers should develop targeted rural infrastructure programs to bridge the digital divide. Given the significant urban-rural disparities in AI awareness and adoption intent, government agency in charge of agriculture should prioritize expanding broadband connectivity, subsidizing AI-enabled devices, and establishing rural digital hubs.
2. Agricultural Extension unit should Implement age- and gender-sensitive training programs. With older farmers showing lower ease-of-use ratings and female farmers demonstrating less trust in AI, extension services should design differentiated training modules.
3. AI Developers and Tech Companies should Co-design simplified interfaces with farmer input. The consistently low ease-of-use scores across demographics and rural farmers' skepticism call for participatory design of voice-enabled, icon-based interfaces in local languages.
4. Farmer Cooperatives and NGOs should Organize localized AI demonstration farms Since perceived benefits strongly predicted adoption intent yet rural benefit recognition lagged, cooperatives should establish model farms showcasing AI applications for weather prediction and pest control.

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