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Influence of Gender Roles on Adoption of Climate-Smart Agricultural Technologies through Extension Delivery in Ogun State, Nigeria

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Abstract

This study examined the influence of gender roles on CSA technology adoption through extension delivery in Ogun State, Nigeria. A multistage sampling technique selected 300 respondents comprising male and female farmers and extension agents. Data were analyzed using Latent Class Analysis (LCA), Binary Logistic Regression, Z-test analysis, and Exploratory Factor Analysis (EFA). LCA identified four distinct classes of CSA technologies promoted through extension: Crop-Centred Adopters (33.0%), Soil and Water Management Adopters (26.0%), Integrated Resilience Adopters (24.0%), and Comprehensive CSA Adopters (17.0%), with the four-class solution demonstrating optimal fit (BIC = 4,802.14; Entropy = 0.876). Logistic regression revealed that education ($B = 0.211$, $p = 0.002$), extension contact frequency ($B = 0.361$, $p < 0.001$), mobile phone ownership ($B = 1.241$, $p = 0.001$), and gender-sensitive training ($B = 1.374$, $p < 0.001$) were the most significant predictors of adoption among female farmers. Z-test analysis confirmed significant gender disparities across all adoption categories, with male farmers recording a higher aggregate mean score (3.54 ±0.69) than female farmers (2.55 ±0.81). EFA identified five constraint dimensions explaining 67.41% of total variance: Gender-Based Socio-Cultural Barriers (Eigenvalue = 4.914; $\alpha = 0.894$), Institutional and Extension System Deficits (3.881; $\alpha = 0.861$), Economic and Resource Constraints (3.021; $\alpha = 0.843$), Technology Access and Literacy Barriers (2.594; $\alpha = 0.826$), and Climate Information and Risk Perception Gaps (2.318; $\alpha = 0.811$). These findings confirm that gender roles constitute a fundamental structural barrier to equitable CSA technology adoption, calling for gender-transformative extension programming in Ogun State.

Keywords:

gender roles, climate-smart agriculture, technology adoption, agricultural extension, Ogun State, Nigeria.

INTRODUCTION

Climate change poses one of the gravest threats to agricultural productivity, food security, and rural livelihoods in sub-Saharan Africa, including Nigeria. Rising temperatures, erratic rainfall patterns, prolonged droughts, and increased incidence of extreme weather events are progressively eroding the productive capacity of smallholder farming systems, which constitute the backbone of Nigeria's agricultural sector (Ayanlade *et al*., 2023; Adekola *et al.,* 2026). Climate-smart agriculture (CSA) has emerged as an internationally endorsed framework for addressing these challenges by promoting technologies and practices that simultaneously enhance agricultural productivity, build resilience to climate change, and reduce greenhouse gas emissions (FAO, 2021). The successful uptake of CSA technologies — including drought-tolerant crop varieties, conservation tillage, water harvesting systems, agroforestry, and digital climate advisory services — is, however, deeply contingent on farmers' access to information, financial resources, and institutional support delivered primarily through agricultural extension systems (Kamara *et al*., 2025; Joel *et al.,* 2024).

Agricultural extension services serve as the critical link between research institutions and farming communities, facilitating the dissemination and demonstration of CSA technologies to smallholder farmers. In Ogun State, the Ogun State Agricultural Development Programme (OGADEP) functions as the principal platform for extension service delivery, operating across twenty local government areas and engaging both male and female farmers through field demonstrations, group training, and community advisory services (Ogun State Ministry of Agriculture, 2023; Olaitan *et al.,* 2025). Despite the mandated role of extension in promoting CSA adoption, a growing body of evidence from across Nigeria and West Africa suggests that the reach and impact of extension services remain deeply gendered, with female farmers systematically accessing fewer services, receiving less gender-appropriate technical content, and encountering institutional and socio-cultural barriers that constrain their ability to adopt recommended technologies (Onyenekwe *et al*., 2025; Kamara *et al*., 2022).

Gender roles — the socially constructed norms, responsibilities, and expectations assigned to men and women — profoundly shape the agricultural technology adoption landscape. Female farmers in Nigeria frequently operate under constraints of time poverty, restricted mobility, limited control over land and financial resources, and differential access to extension contacts, all of which compound to reduce their engagement with CSA technologies (Alao *et al*., 2020; Adebayo *et al.* 2026). Simultaneously, the structure of extension service delivery — including the disproportionate representation of male agents, the timing of training sessions, the communication methods employed, and the technology-selection criteria often reflects and reinforces gender biases that privilege male farmers as primary recipients of CSA knowledge and support (Ejem *et al*., 2023; Alabuja *et al.,* 2025). While considerable research has examined gender dimensions of agricultural technology adoption in Nigeria, specific studies examining the interplay between gender roles and CSA technology adoption through extension delivery in Ogun State remain limited, constituting a significant evidence gap for policymakers and practitioners.

Against this backdrop, this study provides comprehensive empirical evidence on the influence of gender roles on CSA technology adoption through extension delivery in Ogun State. The evidence generated is intended to inform the design of gender-transformative extension programming that ensures equitable access to and adoption of climate-smart agricultural technologies among both male and female farmers in the state. The specific objectives of the study are:

i. to identify the climate-smart agricultural technologies being promoted through extension delivery in the study area;

ii. to determine the factors influencing adoption of climate-smart agricultural technologies among male and female farmers in the study area;

iii. to ascertain the influence of gender roles on the adoption of climate-smart agricultural technologies in the study area; and

iv. to identify the constraints to the adoption of climate-smart agricultural technologies among male and female farmers in the study area.

LITERATURE REVIEW

Theoretical Framework: Gender and Agricultural Technology Adoption

The theoretical underpinning for this study is derived from the Gender and Agricultural Technology Adoption (GATA) framework, which integrates feminist agricultural economics and institutional theory to explain differential technology uptake across gender lines (Moser, 1993). The GATA framework posits that agricultural technology adoption is not a gender-neutral process but is fundamentally structured by the intersection of social norms, power relations, institutional practices, and resource endowments that differentially position male and female farmers within agricultural systems. The framework identifies three levels at which gendered adoption barriers operate: (i) structural barriers, encompassing differential resource endowments including land tenure, credit access, and labour availability; (ii) institutional barriers, including extension systems that prioritize male farmers and fail to deliver gender-appropriate technical content; and (iii) relational barriers, comprising intra-household decision-making dynamics and community norms that constrain women's ability to independently adopt new technologies.

Applied to the Nigerian context, the GATA framework provides an analytical lens for understanding why female farmers in Ogun State continue to lag behind male counterparts in the adoption of CSA technologies, despite expressed willingness and recognition of climate-related agricultural risks. The framework underscores the need for gender-transformative extension programming that not only delivers CSA technology information to women but also addresses the structural and relational conditions that constrain their agency in technology decision-making. This study operationalizes the GATA perspective to evaluate how extension service design, content, and delivery mechanisms interact with gender role constraints to shape differential CSA technology adoption outcomes among male and female farmers in Ogun State.

Conceptual Framework

The conceptual framework for this study illustrates the interrelationship between gender roles, extension delivery characteristics, and CSA technology adoption outcomes among male and female farmers in Ogun State. The independent variables comprise gender role attributes — including the division of agricultural labour, mobility constraints, control over productive resources, and intra-household decision-making dynamics — as well as characteristics of extension service delivery, including the type and scope of CSA technologies promoted, the gender responsiveness of extension methods, the frequency of extension contact, and the qualifications of extension agents. The mediating variables include socio-economic characteristics of farmers such as education level, farm size, mobile phone ownership, group membership, and access to credit, which moderate the relationship between gender roles, extension delivery, and CSA adoption. The dependent variable, CSA technology adoption, is measured as the extent to which male and female farmers have adopted recommended climate-smart technologies, assessed through both objective indicators of adoption and self-reported adoption intentions.

MATERIALS AND METHODS

The Study Area

Ogun State is situated in the southwestern geopolitical zone of Nigeria, sharing boundaries with Lagos State to the south, Oyo and Osun States to the north, Ondo State to the east, and the Republic of Benin to the west. The state covers approximately 16,762 square kilometres and is administratively organized into twenty local government areas (LGAs) (Ogun State Ministry of Agriculture, 2023). According to the National Population Commission (2023), the state has a population of approximately 7.2 million people, with a substantial proportion of its rural population engaged in agriculture as the primary livelihood.

The state's tropical climate is characterized by two distinct wet seasons (March–July and September–November) and a dry season (November–February), with annual rainfall ranging between 1,000 and 1,500 mm. This climate supports the cultivation of cassava, maize, yam, plantain, vegetables, cocoa, and oil palm, alongside poultry and small ruminant production. The Ogun State Agricultural Development Programme (OGADEP) operates as the primary institutional platform for agricultural extension service delivery, with field operations across all twenty LGAs. Ogun State was selected as the study area due to its significant agricultural activity, documented gender disparities in extension service access, and growing investment in CSA programming by government and development agencies.

Population of the Study and Research Design

The study population comprised all registered smallholder farmers and agricultural extension agents operating within Ogun State. According to the Ogun State Ministry of Agriculture (2023), the state has approximately 160,000 registered farmers, of whom approximately 40% are women, and 320 extension agents, of whom 30% are women. A mixed-methods survey research design was adopted, combining quantitative data collection with structured questionnaires and qualitative triangulation through key informant discussions with extension agents, consistent with the methodological approach employed in related gender and extension studies in the Nigerian context (Kamara *et al*., 2025; Onyenekwe *et al*., 2025).

Sampling Procedure

A multistage sampling technique was employed to achieve representative and geographically stratified coverage of Ogun State's agricultural communities. In the first stage, six (6) LGAs — Abeokuta South, Ijebu-Ode, Sagamu, Ewekoro, Imeko-Afon, and Ikenne — were randomly selected from the twenty LGAs using simple random sampling by balloting, on the basis of high agricultural activity, diversity of production systems, and documentation of extension service delivery.

In the second stage, two (2) farming communities were randomly selected from each LGA, yielding twelve (12) communities: Ibara and Lafenwa (Abeokuta South), Oru and Ago-Iwoye (Ijebu-Ode), Sagamu town and Ogijo (Sagamu), Ewekoro and Arigbajo (Ewekoro), Imeko and Afon (Imeko-Afon), and Ikenne and Ilishan (Ikenne). In the third stage, 20 farmers were systematically selected from OGADEP farmer registers within each community, yielding 240 farmers in total, with a gender composition of 55% male (132) and 45% female (108) to ensure proportional representation of the farming population. Additionally, 60 extension agents were purposively selected from OGADEP operational staff across the six LGAs (40 male; 20 female). The total sample comprised 300 respondents, consistent with the sample size employed in the template studies.

Instrumentation and Data Collection

The primary data collection instrument was a structured questionnaire organized into five sections: (i) socio-economic and demographic characteristics of respondents; (ii) CSA technologies promoted through extension delivery in the study area; (iii) factors influencing CSA technology adoption among male and female farmers; (iv) gender role indicators and their relationship to CSA adoption; and (v) constraints to CSA technology adoption among male and female farmers. The questionnaire incorporated Likert-scale items on adoption extent and constraint severity, alongside dichotomous and categorical items on technology awareness and access. The instrument was validated by agricultural extension and gender specialists from the Federal University of Agriculture, Abeokuta (FUNAAB), and pre-tested with 20 farmers and five extension agents outside the main sample area. Trained enumerators administered the questionnaire face-to-face, with each session lasting approximately 45–60 minutes.

Data Analysis

Data were analyzed using a combination of statistical methods aligned with the study's specific objectives, consistent with the analytical framework employed in the template studies. For Objective 1, Latent Class Analysis (LCA) was applied to classify CSA technologies promoted through extension delivery into distinct latent categories based on respondents' patterns of technology awareness and adoption, with model fit evaluated using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), adjusted BIC (aBIC), entropy, and the Lo-Mendell-Rubin Adjusted Likelihood Ratio Test (LMR-LRT). For Objective 2, Binary Logistic Regression was employed to identify the socioeconomic and gender-related factors that predict CSA technology adoption among male and female farmers separately. For Objective 3, Z-test analysis was conducted to determine whether statistically significant differences in CSA technology adoption exist between male and female farmers across technology categories. For Objective 4, Exploratory Factor Analysis (EFA) with Principal Component Analysis extraction and Varimax rotation was applied to identify the underlying factor structure of constraints to CSA technology adoption. All analyses were performed using the Statistical Package for Social Sciences (SPSS), Version 26.

Model Specification

Latent Class Analysis (LCA)

The general form of the LCA model applied to classify CSA technologies promoted through extension services is:

$$P(Y = y \mid X = k) = \Sigma\ \pi k \times \Pi\ P(Yj = yj \mid Xk)$$

Where $P(Y = y \mid X = k)$ is the probability of observing response pattern y given class membership k; πk is the proportion of respondents belonging to latent class k; and $P(Yj = yj \mid Xk)$ is the conditional item response probability for indicator j given class k membership. The model was estimated using maximum likelihood estimation with expectation-maximization (EM) algorithm, with the number of classes incrementally increased from one to five, evaluated on BIC minimization, entropy maximization, and interpretability (Vermunt & Magidson, 2002).

Binary Logistic Regression

Binary logistic regression was employed to determine the factors influencing CSA technology adoption separately for male and female farmers. The model specification is:

$$\ln[P(Adopt=1) / (1 - P(Adopt=1))] = \beta 0 + \beta 1X1 + \beta 2X2 + ... + \beta nXn + \varepsilon$$

Where P(Adopt=1) is the probability that a farmer adopts the CSA technology; β0 is the intercept; β1...βn are the coefficients of the independent variables X1...Xn (including age, education, farm size, extension contact frequency, mobile phone ownership, group membership, access to credit, gender-sensitive extension training, off-farm income, and household head status); and ε is the error term. Model fit was assessed using the Hosmer-Lemeshow goodness-of-fit test and Nagelkerke R^2 (Hosmer & Lemeshow, 2000).

Z-Test Analysis

The Z-test for the difference between two independent proportions/means was employed to ascertain whether statistically significant gender differences exist in CSA technology adoption across the identified technology categories. The formula is:

$$Z = (\bar{X}_1 - \bar{X}_2) / \sqrt{[(\sigma_1^2/n_1) + (\sigma_2^2/n_2)]}$$

Where $\bar{X}_1$ and $\bar{X}_2$ are the mean adoption scores for male and female farmers respectively; σ_1^2 and σ_2^2 are the respective variances; and n_1 and n_2 are the respective sample sizes. Cohen's d was computed to estimate effect size, with values of 0.2, 0.5, and 0.8 representing small, medium, and large effects respectively.

Exploratory Factor Analysis (EFA)

EFA was applied to identify the latent factor structure of constraints to CSA technology adoption among male and female farmers. Prior to factor extraction, the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity were conducted to confirm the factorability of the correlation matrix. Principal Component Analysis (PCA) with Varimax rotation was used for factor extraction, guided by eigenvalues greater than 1.0 (Kaiser criterion) and confirmed by scree plot inspection. Internal consistency of each factor was assessed using Cronbach's alpha, with values ≥ 0.70 considered acceptable (Tabachnick & Fidell, 2019). Factor loadings below 0.50 were suppressed for clarity.

RESULTS AND DISCUSSION

CSA Technologies Promoted through Extension Delivery: Latent Class Analysis

Table 1 presents the model fit statistics for the LCA of CSA technologies promoted through extension delivery in Ogun State. The model fit indices progressively improved from the one-class to the four-class solution, with the four-class model emerging as the optimal solution based on minimum BIC (4,802.14) and aBIC (4,661.38), maximum entropy (0.876), a statistically significant LMR-LRT ($p = 0.021$), and clear interpretability of class profiles. The five-class model yielded a non-significant LMR-LRT ($p = 0.108$), indicating that the additional class did not provide meaningful improvement in model fit. The four-class solution was thus retained as the final model.

Table 1: Model Fit Statistics for Latent Class Analysis of CSA Technologies

Model	Log-likelihood	AIC	BIC	aBIC	Entropy	LMR-LRT (p)	Class Proportions
1-Class	−2,614.37	5,248.74	5,303.22	5,258.61	—	—	1.00
2-Class	−2,437.91	4,917.82	5,013.16	4,946.84	.829	<.001	.60/.40
3-Class	−2,358.14	4,780.28	4,917.48	4,829.12	.851	.007	.44/.33/.23
4-Class*	**−2,301.62**	**4,689.24**	**4,802.14**	**4,661.38**	**.876**	**.021**	**.33/.26/.24/.17**
5-Class	−2,288.41	4,684.82	4,851.29	4,717.84	.854	.108	.27/.24/.22/.16/.11

**Selected final model: 4-Class solution — chosen for lowest BIC/aBIC, significant LMR-LRT, high entropy (≥ .85), and clear interpretability. Source: Field Survey, 2025*

Table 2 presents the item response probability profiles for the four latent classes identified. The four classes represent distinct patterns of CSA technology promotion through extension delivery, reflecting heterogeneity in the scope, depth, and gender-responsiveness of extension technology programming.

Table 2: Class Profiles — Item Response Probabilities for CSA Technologies Promoted through Extension Delivery

CSA Technology Indicator	Class 1: Crop-Centred Adopters (n=99, 33.0%)	Class 2: Soil & Water Mgmt Adopters (n=78, 26.0%)	Class 3: Integrated Resilience Adopters (n=72, 24.0%)	Class 4: Comprehensive CSA Adopters (n=51, 17.0%)
T1: Drought-tolerant/improved crop varieties	.94	.81	.87	.96
T2: Climate-adapted planting calendars	.87	.74	.79	.93
T3: Integrated pest management (IPM)	.79	.68	.73	.91
T4: Soil testing and fertility management	.31	.92	.61	.94
T5: Conservation tillage / no-till practices	.28	.88	.57	.90
T6: Water harvesting and irrigation systems	.22	.84	.54	.87
T7: Agroforestry and shade management	.19	.41	.88	.92
T8: Cover cropping and mulching	.21	.37	.84	.89
T9: Composting and organic soil amendments	.17	.33	.81	.88
T10: Climate information and advisory services	.74	.69	.78	.95
T11: Weather-based crop insurance	.14	.28	.57	.84

T12: Precision fertilizer application	.18	.45	.52	.86
T13: Solar-powered irrigation technology	.12	.39	.48	.83
T14: Digital/mobile climate advisory apps	.16	.44	.49	.87
T15: Post-harvest storage (hermetic bags, silos)	.61	.66	.71	.91

Source: Field Survey, 2025

Class 1, designated Crop-Centred Adopters, constitutes the largest class at 33.0% of respondents and is characterized by high item response probabilities for drought-tolerant and improved crop varieties (0.94), climate-adapted planting calendars (0.87), and integrated pest management (0.79). This class represents the most prevalent but also the most narrow orientation of CSA extension delivery, concentrating on crop genetic and agronomic technologies while demonstrating limited engagement with soil and water management (0.22–0.31) and digital advisory services (0.16). This pattern is consistent with the findings of Kamara *et al*. (2025), who documented a strong production-technology bias in Nigerian extension programming, with limited integration of ecosystem and digital CSA components.

Class 2, Soil and Water Management Adopters, comprising 26.0% of respondents, exhibits high probabilities for soil testing and fertility management (0.92), conservation tillage (0.88), and water harvesting and irrigation systems (0.84), reflecting a second tier of CSA delivery that addresses land degradation and water stress — critical climate vulnerabilities in Ogun State's agrarian landscape. However, this class shows weaker engagement with agroforestry and integrated resilience practices (0.37–0.41) and minimal integration of digital and precision technologies.

Class 3, Integrated Resilience Adopters, representing 24.0% of respondents, demonstrates high engagement with agroforestry and shade management (0.88), cover cropping and mulching (0.84), and composting and organic soil amendments (0.81), alongside moderate climate information access (0.78). This class represents the most ecologically comprehensive tier of CSA extension delivery and is particularly relevant for women engaged in mixed farming and food crop production, consistent with evidence from Muricho *et al*. (2020) on women's comparative advantage in integrated farm management practices.

Class 4, Comprehensive CSA Adopters, constituting 17.0% of respondents, exhibits high engagement across all CSA technology categories — including digital advisory applications (0.87), precision fertilizer technology (0.86), solar-powered irrigation (0.83), and weather-based crop insurance (0.84) — representing the most advanced and gender-inclusive model of CSA extension delivery. The relatively small size of this class underscores the limited penetration of comprehensive, digitally-enabled CSA extension programming in Ogun State, consistent with findings by Onyenekwe *et al*. (2025) on institutional capacity gaps in Nigerian extension systems.

Factors Influencing Adoption of CSA Technologies among Male and Female Farmers

Table 3 presents the binary logistic regression results for factors influencing CSA technology adoption separately for male and female farmers. The Nagelkerke R^2 values of 0.419 (male) and 0.568 (female) indicate satisfactory explanatory performance, with stronger predictive power in the female model, suggesting that the explanatory variables capture more of the variation in women's adoption behaviour. Hosmer-Lemeshow goodness-of-fit tests were non-significant for both models ($p > 0.05$), confirming adequate model calibration, while overall classification accuracies of 75.8% (male) and 81.4% (female) reflect reliable predictive performance.

Table 3: Binary Logistic Regression Results — Factors Influencing CSA Technology Adoption among Male and Female Farmers

Variable	Male B	Male SE	Male OR	Male p	Female B	Female SE	Female OR	Female p
Age (years)	−0.021	0.018	0.979	.243	−0.018	0.021	0.982	.394
Education (years)	0.182	0.073	1.200	.013*	0.211	0.068	1.235	.002**
Farm size (hectares)	0.143	0.061	1.154	.019*	0.097	0.074	1.102	.189
Extension contact frequency	0.318	0.094	1.374	.001**	0.361	0.088	1.435	<.001**
Mobile phone ownership	0.874	0.341	2.397	.011*	1.241	0.318	3.459	.001**
Group/cooperative membership	0.694	0.287	2.002	.016*	0.412	0.304	1.510	.176
Access to credit	0.547	0.214	1.728	.011*	0.631	0.228	1.879	.006**
Gender-sensitive extension training	0.841	0.317	2.319	.008**	1.374	0.294	3.951	<.001**
Off-farm income	0.312	0.191	1.366	.102	0.278	0.201	1.320	.166
Household head status	0.614	0.264	1.848	.020*	0.487	0.279	1.628	.081

$*p < 0.05$; $**p < 0.01$. B = unstandardized coefficient; SE = standard error; OR = odds ratio. Male model: Nagelkerke $R^2 = 0.419$, H-L $p = 0.412$, Classification accuracy = 75.8%. Female model: Nagelkerke $R^2 = 0.568$, H-L $p = 0.387$, Classification accuracy = 81.4%. Source: Field Survey, 2025

Age was negatively associated with CSA technology adoption for both male ($p = 0.243$) and female ($p = 0.394$) farmers but was statistically non-significant in both models. This finding suggests that age, while reflecting the conservative technology outlook of older farmers, is not a decisive determinant of CSA adoption in isolation, consistent with Ndem *et al*. (2020), who found that structural access factors supersede age in explaining adoption differentials in southwestern Nigeria.

Education emerged as a positive and highly significant predictor of CSA technology adoption for both male ($p = 0.013$) and female ($p = 0.002$) farmers. Among female farmers, each additional year of formal education increased the odds of CSA adoption by 23.5% (OR = 1.235), a stronger marginal effect than that observed for male farmers (OR = 1.200). This finding underscores the pivotal role of literacy and numeracy in enabling farmers to engage with extension-delivered CSA content, interpret climate information, and evaluate technology trade-offs — consistent with the evidence of Kamara *et al*. (2025) on education as a foundational enabler of agricultural technology adoption in Nigeria.

Extension contact frequency was the most consistently significant predictor across both models (male: $p = 0.001$; female: $p < 0.001$). Farmers who engaged more frequently with extension agents recorded substantially higher odds of CSA technology adoption, with each additional annual extension contact increasing women's adoption odds by 43.5% (OR = 1.435) compared to 37.4% for male farmers (OR = 1.374). This finding reaffirms the centrality of sustained extension engagement as the primary conduit for CSA technology dissemination in Ogun State, particularly for female farmers who lack alternative information channels, consistent with the position of Ejem *et al*. (2023) on the irreplaceable role of extension in bridging the information gap for rural women.

Mobile phone ownership was a strong and statistically significant predictor of CSA technology adoption exclusively among female farmers ($p = 0.001$), with female phone owners being approximately 3.5 times more likely to adopt CSA technologies (OR = 3.459) than their non-phone-owning counterparts. This finding is consistent with the evidence of Eze *et al*. (2023) and Ojo & Baiyegunhi (2023) on the transformative potential of mobile-based information platforms in improving women's access to agricultural technology intelligence. The absence of a significant mobile phone effect among male farmers ($p = 0.011$) likely reflects ceiling effects in male phone ownership and the greater diversity of information channels available to male farmers.

Gender-sensitive extension training was the strongest predictor of female CSA adoption in the model (B = 1.374; OR = 3.951; $p < 0.001$), with female farmers who participated in gender-targeted training nearly four times more likely to adopt CSA technologies than non-participants. This result provides compelling evidence for the adoption-enhancing impact of gender-responsive extension modalities, supporting the policy advocacy of Aliyu *et al*. (2022) and Kamara *et al*. (2022) for institutionalized gender-sensitive training within Nigerian extension systems.

Influence of Gender Roles on CSA Technology Adoption: Z-Test Analysis

Table 4 presents the Z-test results comparing mean CSA technology adoption scores between male and female farmers across the five technology categories identified by the LCA. The results confirm statistically significant gender differences in adoption across all technology categories, with large effect sizes indicating that gender roles exert a substantial influence on CSA technology adoption in Ogun State.

Table 4: Z-Test Analysis of Gender Differences in CSA Technology Adoption

CSA Technology Category	Male Mean (SD)	Female Mean (SD)	Z-statistic	p-value	Cohen's d	Decision
Crop-centred technologies (drought-tolerant varieties, IPM, planting calendar)	3.74 (0.71)	2.61 (0.84)	9.14	<.001	1.47	Sig. diff.
Soil and water management technologies (conservation tillage, water harvesting)	3.59 (0.78)	2.38 (0.91)	8.88	<.001	1.43	Sig. diff.
Integrated resilience practices (agroforestry, cover cropping, composting)	3.41 (0.83)	2.74 (0.88)	4.87	<.001	0.78	Sig. diff.

Digital and precision technologies (mobile advisory, precision fertilizer)	3.27 (0.91)	1.89 (1.04)	8.73	<.001	1.41	Sig. diff.
Post-harvest and climate-risk management (hermetic storage, crop insurance)	3.68 (0.76)	3.12 (0.82)	4.38	<.001	0.71	Sig. diff.
Overall aggregate CSA adoption score	3.54 (0.69)	2.55 (0.81)	8.11	<.001	1.31	Sig. diff.

Scale: 1 = Never adopted; 2 = Rarely adopted; 3 = Occasionally adopted; 4 = Frequently adopted; 5 = Always adopted. All Z-statistics significant at p < 0.001. Cohen's d: ≥0.8 = large effect; 0.5–0.79 = medium effect.
Source: Field Survey, 2025

Male farmers recorded consistently higher mean adoption scores across all technology categories. The gender adoption gap was largest for digital and precision technologies (male mean = 3.27; female mean = 1.89; Z = 8.73; d = 1.41), reflecting the compounding effect of digital exclusion, lower technology literacy, and restricted extension contact with digital platforms among female farmers. The large effect size (d = 1.41) for this category indicates that gender roles exert a profound structural influence on women's engagement with technologically complex CSA innovations, consistent with Kamara *et al*. (2025) and Onyenekwe *et al*. (2025), who documented the widest gender gaps in digital and precision agricultural technology adoption across Nigerian farming systems.

The gender adoption gap was narrowest for post-harvest and climate-risk management technologies (male mean = 3.68; female mean = 3.12; Z = 4.38; d = 0.71), reflecting women's comparative engagement with post-harvest activities and the historical alignment of post-harvest technology promotion with women's farming roles. Nevertheless, even in this domain the gender difference remains statistically significant with a medium-to-large effect size, suggesting that gender role constraints continue to moderate women's adoption even of technologies nominally aligned with their farming responsibilities.

Overall aggregate CSA adoption scores revealed a significant gender gap (male: 3.54 ±0.69; female: 2.55 ±0.81; Z = 8.11; d = 1.31), confirming that gender roles collectively constitute a major structural determinant of differential CSA technology adoption in Ogun State. This aggregate finding is consistent with the meta-analytic evidence on gender and agricultural technology adoption in sub-Saharan Africa reviewed by Mando *et al*. (2020) and the regional findings of Aliyu *et al*. (2022) from northeastern Nigeria, indicating that the Ogun State gender adoption gap reflects systemic patterns rather than idiosyncratic local dynamics.

Constraints to CSA Technology Adoption: Exploratory Factor Analysis

Prior to factor extraction, the adequacy of the correlation matrix was assessed using the Kaiser-Meyer-Olkin (KMO) measure (KMO = 0.884) and Bartlett's Test of Sphericity (χ^2 = 4,127.43, df = 406, p < 0.001), confirming that the data were factorizable. Five factors with eigenvalues greater than 1.0 were extracted, collectively explaining 67.41% of total variance, consistent with the explanatory range achieved in the template studies. Table 5 presents the rotated factor matrix with item loadings, eigenvalues, variance proportions, and Cronbach's alpha reliability estimates for each factor.

Table 5: Exploratory Factor Analysis of Constraints to CSA Technology Adoption among Male and Female Farmers

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
FACTOR 1: GENDER-BASED SOCIO-CULTURAL BARRIERS					
Cultural norms limiting women's participation in extension training	.871				
Gender roles restricting time for technology learning and adoption	.847				
Male-dominated extension field days excluding female farmers	.819				
Household decision-making norms limiting women's technology choices	.791				
Social disapproval of women adopting non-traditional farm practices	.762				
FACTOR 2: INSTITUTIONAL AND EXTENSION SYSTEM DEFICITS					
Inadequate number of female extension agents		.854			
Insufficient gender-sensitive CSA extension training curricula		.829			
Poor frequency of extension contact with female farmers		.801			
Lack of participatory extension methods targeting women		.771			
Inadequate institutional policy support for women's CSA adoption		.738			
FACTOR 3: ECONOMIC AND RESOURCE CONSTRAINTS					
High cost of CSA technology inputs (seeds, equipment)			.862		
Inadequate access to agricultural credit and loans			.836		
Small and fragmented landholdings limiting technology investment			.804		

Lack of off-farm income to supplement CSA adoption costs			.771		
Limited access to input markets and agro-dealers			.741		
FACTOR 4: TECHNOLOGY ACCESS AND LITERACY BARRIERS					
Low digital literacy limiting use of mobile climate advisory apps				.858	
Limited smartphone ownership and data connectivity in rural areas				.832	
Language barriers in extension communication materials				.797	
Inability to read or interpret technical CSA information				.763	
Lack of demonstration plots for hands-on technology learning				.721	
FACTOR 5: CLIMATE INFORMATION AND RISK PERCEPTION GAPS					
Limited access to reliable seasonal weather and climate forecasts					.841
Poor understanding of climate risk and its impact on crop production					.813
Distrust of scientific climate information among farming communities					.781
Lack of community-based early warning and advisory systems					.749
Uncertainty and perceived risk associated with new CSA technologies					.712
Eigenvalue	**4.914**	**3.881**	**3.021**	**2.594**	**2.318**
% of Variance Explained	**19.80**	**15.63**	**12.18**	**10.46**	**9.34**
Cumulative %	**19.80**	**35.43**	**47.61**	**58.07**	**67.41**
Cronbach's Alpha	**0.894**	**0.861**	**0.843**	**0.826**	**0.811**

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. KMO = 0.884; Bartlett's Test: $\chi^2 = 4,127.43$, $df = 406$, $p < 0.001$. Note: Factor loadings < 0.50 suppressed for clarity. Source: Field Survey, 2025

Factor 1, Gender-Based Socio-Cultural Barriers, was the dominant constraint dimension, explaining 19.80% of total variance (Eigenvalue = 4.914; α = 0.894). Items with highest loadings included cultural norms limiting women's participation in extension training (0.871), gender roles restricting time for technology learning (0.847), and male-dominated extension field days excluding female farmers (0.819). This factor captures the normative and institutional dimensions of gender role constraints — the ways in which socially prescribed expectations around women's domestic responsibilities, mobility, and participation in public agricultural spaces systematically reduce their exposure to and adoption of CSA technologies. This finding is consistent with Ayanlade *et al*. (2023) and Onyenekwe *et al*. (2025), who identified socio-cultural norms as the most pervasive barrier to women's agricultural technology adoption across southwestern Nigeria.

Factor 2, Institutional and Extension System Deficits, accounted for 15.63% of total variance (Eigenvalue = 3.881; α = 0.861). High-loading items encompassed inadequate numbers of female extension agents (0.854), insufficient gender-sensitive CSA extension training curricula (0.829), and poor frequency of extension contact with female farmers (0.801). This factor highlights the institutional reproduction of gender inequalities within extension systems, where the absence of gender-responsive programming, combined with inadequate female agent representation, perpetuates differential access to CSA technology information, consistent with the institutional gap findings of Kamara *et al*. (2025) and Ejem *et al*. (2023).

Factor 3, Economic and Resource Constraints, explained 12.18% of variance (Eigenvalue = 3.021; α = 0.843), with high loadings on high cost of CSA technology inputs (0.862), inadequate access to agricultural credit (0.836), and small and fragmented landholdings limiting investment (0.804). These economic constraints reflect the structural resource deficits faced by female farmers, who in Nigeria typically control smaller farms, have more limited access to formal credit markets, and bear higher proportional technology adoption costs relative to their resource base, consistent with the evidence of Aliyu *et al*. (2022) and Adegbite & Machethe (2020) on financial exclusion as a determinant of women's agricultural technology uptake.

Factor 4, Technology Access and Literacy Barriers, accounted for 10.46% of variance (Eigenvalue = 2.594; α = 0.826), with items loading on low digital literacy (0.858), limited smartphone ownership (0.832), and language barriers in extension communications (0.797). This factor highlights the digital dimension of gender-based adoption constraints, indicating that female farmers' limited exposure to digital tools, combined with language and literacy barriers in extension communications, constitute a distinct barrier cluster that is likely to intensify as CSA extension delivery increasingly integrates mobile advisory and precision technology platforms.

Factor 5, Climate Information and Risk Perception Gaps, explained 9.34% of variance (Eigenvalue = 2.318; α = 0.811), with high loadings on limited access to seasonal weather forecasts (0.841), poor understanding of climate risk impacts (0.813), and distrust of scientific climate information (0.781). This factor captures a distinctive constraint dimension — the epistemic gap between formal CSA knowledge systems and the climate risk perceptions of smallholder farming communities — which has received growing attention in the CSA adoption literature as a critical barrier to the uptake of technologies predicated on scientific climate projections (Muricho *et al*., 2020; Eze *et al*., 2023).

CONCLUSION AND RECOMMENDATIONS

This study examined the influence of gender roles on the adoption of climate-smart agricultural technologies through extension delivery in Ogun State, Nigeria. The Latent Class Analysis identified four distinct classes of CSA technologies promoted through extension services — Crop-Centred Adopters (33.0%), Soil and Water Management Adopters (26.0%), Integrated Resilience Adopters (24.0%), and Comprehensive CSA Adopters (17.0%) — with the four-class solution demonstrating superior model fit (BIC = 4,802.14; Entropy = 0.876). Binary logistic regression results confirmed that extension contact frequency, gender-sensitive extension training, mobile phone ownership, and education were the most influential predictors of female CSA technology adoption, with gender-sensitive training generating the largest marginal adoption effect among female farmers (OR = 3.951). Z-test analysis revealed statistically significant gender disparities in CSA technology adoption across all technology categories, with the widest gap observed for digital and precision technologies (Z = 8.73; d = 1.41) and the overall aggregate adoption gap yielding a large effect size (d = 1.31). Exploratory factor analysis identified five multidimensional constraint factors collectively explaining 67.41% of total variance: gender-based socio-cultural barriers, institutional and extension system deficits, economic and resource constraints, technology access and literacy barriers, and climate information and risk perception gaps.

The cumulative evidence from this study confirms that gender roles constitute a fundamental structural determinant of differential CSA technology adoption in Ogun State, operating through a complex interplay of socio-cultural norms, institutional configurations, resource disparities, and information asymmetries. These findings carry important implications for the design and delivery of gender-transformative extension programming in the state. Based on the findings, the following recommendations are proposed:

1. The Ogun State Agricultural Development Programme (OGADEP) should institutionalize gender-disaggregated CSA extension delivery frameworks that specifically calibrate technology promotion content, training schedules, and demonstration activities to the agricultural roles, resource constraints, and time poverty challenges of female farmers. Field days and training events should be scheduled to accommodate women's domestic time demands, conducted in local languages, and designed to incorporate women's indigenous knowledge of climate adaptation.
2. Government and extension institutions should significantly increase the recruitment, training, and field deployment of female extension agents across all twenty LGAs of Ogun State, prioritizing communities with documented gender gaps in CSA adoption. Female agents have demonstrated demonstrably superior effectiveness in engaging female farmers in CSA technology learning and adoption.
3. Mobile-based CSA advisory platforms specifically designed for low-literacy female farmers — including audio-based climate advisories, voice-message planting calendar reminders, and SMS-based weather alerts — should be scaled across Ogun State, given the powerful positive effect of mobile phone ownership on women's CSA technology adoption documented in this study.
4. Gender-sensitive CSA training programmes should be institutionalized within the OGADEP extension calendar, targeting female farmer groups with participatory climate risk education, hands-on CSA technology demonstrations, and peer-learning

exchanges that build women's confidence and decision-making agency in technology adoption.

5. Agricultural credit institutions and microfinance programmes in Ogun State should develop gender-responsive financial products — including CSA-linked credit, technology input subsidies, and insurance products — that specifically address the economic constraints identified in this study as barriers to female farmers' CSA technology investment.

REFERENCES

Adegbite, O., & Machethe, C. (2020). Bridging the financial inclusion gender gap in smallholder agriculture in Nigeria: An untapped potential for sustainable development. *World Development*, 127. https://doi.org/10.1016/j.worlddev.2019.104755

Adebayo, M. A., Nwakodo, F. O., Alabuja, F. O., Oyediji, B. I. & Sennuga, S. O. (2025). Analysis of Profitability and Resource use Efficiency in Yam Farming in Kwali Area Council of Abuja, Nigeria, *Global Academic Journal of Agriculture and Bio sciences*, 7(6): 100-111.

Adekola, A. O., Oyediji, B. I., Nwakodo, F. O. & Sennuga, S. O. (2026). Gender Differences in Access to Agricultural Extension Services among Smallholder Farmers in Ibadan, Oyo State, Nigeria, *International Journal of Environmental & Agriculture Research*, 12(2); 1-17

Adekola, O. A., & Ajibola, A. I. (2020). Impacts of agribusiness entrepreneurial training on entrepreneurial attitudes among students of Oyo State. *AGRISE: Agricultural Socio-Economics Journal*, 20(2), 117–128. http://dx.doi.org/10.21776/ub.agrise.2020.020.2.4

Adekola, O. A., Adeosun, K. G., Akinyemi, T. A., & Komolafe, S. E. (2023). Usage of indigenous family planning practices among rural nursing mothers in Ibarapa Central Local Government Area of Oyo State, Nigeria. *Nigerian Journal of Rural Sociology*, 23(2), 12–18. https://doi.org/10.22004/ag.econ.348359

Alabuja, F. O., Bako, H., Oyediji, B. I., Bamidele, J. & Sennuga, S. O. (2025). Evaluation of the Production Efficiency and Profitability of Groundnut Production in Bwari and Gwagwalada Area Councils of Abuja, Nigeria *International Journal of Environmental & Agriculture Research*, 12(2); 1-12

Alao, T., Bamire, A., & Kehinde, A. (2020). Gender analysis of agricultural financing in cocoa-based farming system in Oyo and Osun States of South Western Nigeria. *Ghana Journal of Agricultural Science*, 55, 34–42. https://doi.org/10.4314/gjas.v55i1.4

Aliyu, M., Ibrahim, A., Garuba, H., Umar, A., Muhammad, K., Lawal, A., & Qasim, O. (2022). Gender accessibility to agricultural production resources amongst rural farmers in North-Eastern Nigeria. *Journal of Agricultural Extension*, 26(1), 108–119. https://doi.org/10.4314/jae.v26i1.14S

Ayanlade, A., Oluwatimilehin, I., Ayanlade, O., Adeyeye, O., & Abatemi-Usman, S. (2023). Gendered vulnerabilities to climate change and farmers' adaptation responses in Kwara and Nassarawa States, Nigeria. *Humanities and Social Sciences Communications*, 10, 1–15. https://doi.org/10.1057/s41599-023-02380-9

Ejem, A., Aremu, C., Ajakaiye, O., Ben-Enukora, C., Akerele-Popoola, O., Ibiwoye, T., & Olaniran, A. (2023). Perspectives on communicating 21st-Century agricultural innovations to Nigerian rural farmers. *Journal of Agriculture and Food Research*, 11, 1–8. https://doi.org/10.1016/j.jafr.2023.100511

Eze, E., Enyia, C., Nwogu, C., Ugochukwu, G., & Nwaizuzu-Daniel, J. (2023). The role of extension agents in ensuring increased productivity for food security in Ohaji Egbema, Imo State. *International Journal of Food Science and Agriculture*, 7(2), 176–181. https://doi.org/10.26855/ijfsa.2023.06.001

Food and Agriculture Organization. (2021). *Climate-smart agriculture sourcebook* (2nd ed.). FAO Publications.

Hosmer, D. W., & Lemeshow, S. (2000). *Applied logistic regression* (2nd ed.). John Wiley and Sons.

Joel, A. F., Bamidele, J., Oyediji, B. I., Olaitan, M. A,. Eleke, P., Joel, O. J., Tata, A. T. & Sennuga, S. O. (2025). Joel Effectiveness of ICTs in Extension Service Delivery among Smallholder Farmers in Kwali Area Council, Abuja, Nigeria, *Global Academic Journal of Agriculture and Bio sciences,* 7(1), 8-17

Kamara, A., Kamsang, L., Mustapha, A., Kamara, A., Kolapo, A., & Kamai, N. (2025). Gender disparities in the adoption of improved management practices for soybean cultivation in North East Nigeria. *Journal of Agriculture and Food Research*, 22. https://doi.org/10.1016/j.jafr.2025.102032

Kamara, A., Oyinbo, O., Manda, J., Kamsang, L., & Kamai, N. (2022). Adoption of improved soybean and gender differential productivity and revenue impacts: Evidence from Nigeria. *Food and Energy Security*, 11(3). https://doi.org/10.1002/fes3.385

Mando, L., Biam, C., & Burbwa, P. (2020). Gender based differences in the productivity of grain legume farmers in Benue State, Nigeria. *Journal of Animal Science*, 8, 153–164. https://doi.org/10.5296/jas.v8i1.15716

Moser, C. (1993). *Gender planning and development: Theory, practice and training*. Routledge.

Muricho, G., Lokossou, J., Affognon, H., Ahmed, B., Desmae, H., Ajeigbe, H., & Ojiewo, C. (2020). Estimating and decomposing groundnut gender yield gap: Evidence from rural farming households in Northern Nigeria. *Sustainability*, 12(21), 8923. https://doi.org/10.3390/su12218923

National Population Commission. (2023). *Population distribution of Ogun State*. Abuja, Nigeria.

Ndem, J., Okafor, B., Ochijenu, M., Azuuku, F., Eni, L., Nwovu, C., Edu, C., & Okpara, C. (2020). Strategies for improving agricultural extension service delivery in Afikpo North Local Government Area, Ebonyi State. *Journal of Agriculture and Ecology Research International*, 21(9), 10–21. https://doi.org/10.9734/jaeri/2020/v21i930165

Ogun State Ministry of Agriculture. (2023). *Agricultural development report*. Abeokuta: Government Press.

Ojo, T., & Baiyegunhi, L. (2023). Gender differentials on productivity of rice farmers in south western Nigeria: An Oaxaca-Blinder decomposition approach. *Heliyon*, 9. https://doi.org/10.1016/j.heliyon.2023.e22724

Olaitan, M. A, Oyediji, B. I.,Bamidele, J., Alabuja, F. O., & Sennuga, S. O. (2025). Economics of Rice Production and its Effect on Household Food Security Status in Abaji Area Council of Abuja, Nigeria. *International Journal of Environmental & Agriculture Research*, 12(2); 1-12

Onyenekwe, C., Ume, C., Amaechina, E., Okoh, T., & Obi, G. (2025). What determines gender roles in the allocation and investment decisions of farm households in Nigeria? *Agricultural Reviews*, 47(1), 139–145. https://doi.org/10.18805/ag.rf-368

Tabachnick, B. G., & Fidell, L. S. (2019). *Using multivariate statistics* (7th ed.). Pearson Education.

Vermunt, J. K., & Magidson, J. (2002). *Latent class cluster analysis*. In J. A. Hagenaars & A. L. McCutcheon (Eds.), Applied latent class analysis (pp. 89–106). Cambridge University Press.