

Empirical Analysis of Socio-economic and Perceptual Factors Governing Agro-Advisory Uptake Among Paddy Cultivators

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Received: 12-10-2025

Revised: 29-11-2025

Accepted: 06-12-2025

ABSTRACT

This study empirically investigates the socio-economic, digital, and perceptual factors governing agro-advisory uptake among paddy (*Oryza sativa*) cultivators. Using a multi-stage sampling strategy, primary data were collected through face-to-face personal interviews from 120 active paddy farmers ($N = 120$). The study used Ordinary Least Squares (OLS) regression to analyze the determinants of advisory utilization intensity. Descriptive findings show that while 73.3% ($n = 88$) of respondents acknowledged a perceived need for agro-advisories, 55.0% ($n = 66$) exhibited low practice utilization, highlighting a pronounced “know-do gap”. Econometric estimations ($R^2 = 0.584$, $p < 0.001$) revealed that internet access ($\beta = 3.942$, $p < 0.001$) was the strongest positive driver of advisory utilization. Perceived need ($\beta = 2.415$, $p < 0.001$), formal education level ($\beta = 0.481$, $p = 0.012$), and net annual household income ($\beta = 0.000012$, $p = 0.008$) also significantly enhanced utilization scores. Conversely, age showed a statistically significant negative association ($\beta = -0.043$, $p = 0.028$), indicating lower advisory uptake among older farming cohorts. Gender and family size did not directly influence utilization intensity. Overall, the results demonstrate that information access alone is insufficient for practice change unless supported by digital infrastructure and financial capability. To prevent digital exclusion, extension policy must move toward hybrid (“phygital”) extension frameworks that integrate digital/SMS communication with field-level extension support, alongside aligning advisories with input credit programs.

Keywords: Agro-advisory uptake, Digital Extension, Econometric Modeling, Know-do-Gap, Paddy Cultivators, Smallholder Adoption

Paddy (*Oryza sativa*) is a foundational staple crop vital to global food security and rural livelihoods across developing agrarian economies. However, paddy cultivators face escalating challenges, including climate volatility, emerging pest and disease dynamics, rising input costs, and shifting market structures. In this context, agricultural extension and advisory services—spanning traditional field extension, weather-based agrometeorological

guidance, and digital cyber-extension channels—serve as critical conduits for transferring research-backed agronomic interventions and real-time decision support directly to farm households.

How to cite this article: Minz, A.D., Demta, S.S., Kumar, R. and Shyamrao, I.D. (2025). Empirical Analysis of Socio-economic and Perceptual Factors Governing Agro-Advisory Uptake Among Paddy Cultivators. *Agro Economist - An International Journal*, 12(04): 187-196.

Source of Support: None; **Conflict of Interest:** None 

Despite the expanding availability of agricultural advisories, a persistent challenge in agricultural extension is the “know-do gap”: the structural disconnect between farmers’ awareness or perceived need for information and their actual field-level utilization of recommended practices. While traditional economic models assumed that information access directly leads to technology adoption, contemporary empirical evidence demonstrates that information uptake is a complex process governed by socio-demographic drivers, financial liquidity, digital infrastructure, and cognitive perceptions.

While prior research has broadly evaluated agricultural advisory services, empirical studies examining the interactive effect between digital internet access, individual perception of need, and socio-economic constraints within localized paddy production systems remain limited. Specifically, there is a critical need to evaluate how digital exclusion interacts with traditional factors like age, formal education, and household income to dictate whether a farmer transitions from recognizing a need for advice to actively implementing it.

To address this research gap, this study provides an empirical analysis of paddy cultivators ($N = 120$) to evaluate the socio-economic and perceptual drivers governing agro-advisory uptake. The primary objectives of this paper are threefold:

- (i) To profile the socio-demographic and digital connectivity status of paddy farmers within the target ecosystem.
- (ii) To quantify the extent of perceived need and actual utilization tiers among smallholder producers.
- (iii) To econometrically isolate the primary socio-economic, digital, and perceptual determinants that drive or inhibit agro-advisory utilization using Ordinary Least Squares (OLS) and Binary Logistic Regression frameworks.

By bridging empirical field data with contemporary extension literature, the findings of this study provide actionable insights for policymakers, extension agencies, and ag-tech developers striving

to design inclusive, climate-resilient, and digitally accessible advisory frameworks.

METHODS

Research Design and Sampling Strategy

This study adopted an empirical, quantitative cross-sectional research design to investigate the socio-economic, technological, and perceptual drivers governing the uptake of agro-advisory services among paddy (*Oryza sativa*) cultivators of Garhwa district of Jharkhand.

A multi-stage sampling technique was utilized to select $N = 120$ active paddy farmers. Primary data collection was conducted through face-to-face, structured personal interviews using a pre-tested interview schedule. Face-to-face administration was chosen over digital or remote surveys to eliminate non-response bias and ensure accurate data capture across varying formal literacy levels. Prior to full-scale data collection, the survey instrument was pilot-tested on a non-sample group of 15 paddy farmers to establish construct clarity, logical sequencing, and face validity. The research was carried out in the year 2024-25.

Variable Operationalization and Measurement Framework

The empirical variables investigated were categorized into socio-demographic predictors, digital connectivity indicators, a perceptual mediator, and the primary adoption outcome variable.

Independent Variables

- ♦ **Age:** Operationalized as a continuous ratio variable measured in completed chronological years. Age serves as a proxy for farming experience as well as potential risk aversion toward new technologies.
- ♦ **Gender:** Captured as a binary categorical variable to assess gender-differentiated access to agricultural information channels.
- ♦ **Educational Attainment:** Operationalized as a 6-point ordinal construct reflecting formal education completed.

- ♦ **Family Size:** Recorded as a continuous ratio variable representing the total number of individuals cohabiting in the household. This serves as a proxy for family labor availability.
- ♦ **Annual Household Income:** Measured as a continuous numerical variable representing net annual income (expressed in local currency unit, LCU) derived from crop production, livestock, and off-farm agricultural enterprise.
- ♦ **Internet Access:** Measured as a binary dummy variable (0 = No Access, 1 = Access) indicating functional access to digital information infrastructure via internet-enabled devices (smartphones, tablets, or computers).

Perceptual and Outcome Variables

- ♦ **Perceived Need:** Captured as a binary construct (0 = Need Not Perceived, 1 = Need Perceived) evaluating whether the farmer subjectively acknowledges a necessity for real-time agro-advisory inputs (e.g., weather forecasts, pest/disease management, fertilizer scheduling).
- ♦ **Utilisation:** Evaluated using a 15-item composite score ranging from 14 to 29, where higher scores reflect higher frequency and depth of adopting extension recommendations.

To preserve maximum statistical variance during regression modeling, the raw continuous score (14– 29) was retained. Additionally, for non-parametric evaluation and cross-tabulation, scores were segmented into three ordinal adoption tiers based on distribution cut-offs:

- ♦ *Low Utilisation:* Score range 14 to 18 (Inconsistent or non-adoption).
- ♦ *Medium Utilisation:* Score range 19 to 23 (Partial/selective adoption).
- ♦ *High Utilisation:* Score range 24 to 29 (Consistent, comprehensive adoption).

Econometric and Statistical Modelling Framework

Data processing and econometric estimations were executed using statistical computing software. The analytical workflow followed a three-phase structure:

descriptive profiling, bivariate tests of association, and multivariate econometric regressions.

Diagnostic Testing and Model Assumptions

Prior to running parametric models, data distributions were evaluated for classical linear regression assumptions:

- ♦ **Multicollinearity:** Evaluated using the Variance Inflation Factor (VIF) and Tolerance metrics. Variables exhibiting $VIF > 5.0$ or $Tolerance < 0.20$ were slated for removal or transformation to prevent inflated standard errors.
- ♦ **Heteroscedasticity:** Tested using the Breusch-Pagan / Cook-Weisberg test to verify constant variance (σ^2) in regression residuals.

Normality of Residuals: Assessed via the Shapiro-Wilk test and visual inspection of Normal P-P plots.

Model 1: Binary Logistic Regression (Determinants of Perceived Need)

To model the qualitative choice of whether a farmer perceives a need for agro-advisories ($PERCEIVED_NEED = 1$), a Binary Logistic Regression model was specified. The logit transformation of the underlying probability P_i is expressed as:

$$\text{logit}(P_i) = \ln\left(\frac{P_i}{1 - P_i}\right)$$

$$\ln\left(\frac{P_i}{1 - P_i}\right) = \beta_0 + \beta_1 AGE_i + \beta_2 GENDER_i + \beta_3 EDU_i + \beta_4 FAM_SIZE_i + \beta_5 INCOME_i + \beta_6 INT_ACCESS_i + \varepsilon_i$$

Where:

P_i is the probability that the i^{th} farmer perceives a need for advisory services.

$\frac{P_i}{1 - P_i}$ represents the odds ratio.

β_0 is the intercept term, $\beta_1 \dots \beta_6$ are slope coefficients, and ε_i is the stochastic error term.

Model 2: Multiple Linear Regression (Determinants of Utilisation Score)

To determine the direct socio-economic and

perceptual drivers governing the intensity of advisory utilization, an Ordinary Least Squares (OLS) Multiple Linear Regression was specified using the raw continuous index (14–29):

$$UTILISATION_i = \alpha_0 + \alpha_1 AGE_i + \alpha_2 GENDER_i + \alpha_3 EDU_i + \alpha_4 FAM_SIZE_i + \alpha_5 INCOME_i + \alpha_6 INT_ACCESS_i + \alpha_7 PERCEIVED_NEED_i + \mu_i$$

Where α_0 is the model constant, $\alpha_1 \dots \alpha_7$ represent partial regression coefficients indicating the change in utilization score per unit change in the respective predictor, and $\mu_i \sim N(0, \sigma^2)$ represents normally distributed error terms.

Robustness Check: Ordered Logistic Regression

To confirm that model outputs are not distorted by potential non-linearities in the continuous scale, a secondary Ordered Logit (Proportional Odds) model was estimated using the categorical tiers (1 = Low, 2 = Medium, 3 = High). The cumulative logit for category j is formulated as:

$$\ln \left(\frac{P(UTILISATION_i \leq j)}{P(UTILISATION_i > j)} \right) = \theta_j - \left(\sum_{k=1}^K \gamma_k X_{ik} \right)$$

Where θ_j represents the threshold (cut-point) for category j , and γ_k represents the log-odds coefficients for the vector of independent variables X . The proportional odds assumption was formally verified using Brant's Test.

RESULTS

Socio-demographic & Digital Profile of Respondents

The socio-economic and digital characteristics of the sampled 120 paddy farmers ($N = 120$) are summarized in Table 1. The mean age of the respondents was 42.1 ± 14.5 years (ranging from 18 to 85 years). Female farmers constituted 54.2% ($n = 65$) of the sample, while male farmers accounted for 45.8% ($n=55$). Household size averaged 6.3 ± 2.2 members per farm family.

In terms of formal education, 28.3% ($n=34$) of the sample were illiterate, 12.5% ($n=15$) attained primary education, 30.8% ($n=37$) completed middle school,

14.2% ($n=17$) completed higher secondary, 7.5% ($n=9$) completed intermediate, and 6.7% ($n=8$) held a college degree. Annual household income varied widely across the sample, ranging from ₹ 70,000 to ₹ 6,75,000, with an overall mean of ₹ 1,81,420 (SD = ₹ 96,840). Digital connectivity remained limited, as only 31.7% ($n=38$) of farmers reported functional internet access via personal smart devices, whereas 68.3% ($n=82$) lacked internet connectivity.

Table 1: Socio-demographic and Digital Profile of Sampled Paddy Farmers ($N=120$)

Variable Category	Categorical Breakdown/ Unit	Frequency (n)	Percentage (%)	Mean SD
Age	Years	—	—	
Gender	Male	55	45.8%	—
	Female	65	54.2%	—
Family Size	Members	—	—	
Education Level	Illiterate	34	28.3%	—
	Primary School	15	12.5%	—
	Middle School	37	30.8%	—
	Higher Secondary	17	14.2%	—
	Intermediate	9	7.5%	—
	College	8	6.7%	—
	Education			
Annual Income	Currency Units (₹)	—	—	
Internet Access	No Access	82	68.3%	—
	Internet Access	38	31.7%	—

Perceived Need and Advisory Utilisation Levels

A majority of the farmers (73.3%, $n=88$) expressed a positive perception of need for agro-advisory services, while 26.7% ($n=32$) indicated no perceived necessity.

The composite utilization score spanned from a minimum of 14 to a maximum of 29, with an overall sample mean of 18.82 ± 3.61 . When categorized into adoption tiers:

- ♦ Low Utilisation: 55.0% ($n=66$)
- ♦ Medium Utilisation: 37.5% ($n=45$)
- ♦ High Utilisation: 7.5% ($n=9$)

A Chi-Square test of independence revealed a statistically significant association between Perceived Need and Adoption Tier $\chi^2 = 14.86$, $p < 0.001$. However, among the 88 farmers who perceived a need, 47.7% ($n=42$) remained in the Low Utilisation tier, highlighting a noticeable “know-do gap” driven by structural constraints.

Table 2: Distribution of Perceived Need and Utilisation Tiers ($N=120$)

Variable	Classification	Count (n)	Percentage (%)	Mean Score
Perceived Need	Need Not Perceived	32	26.7%	16.1±2.4
	Need Perceived	88	73.3%	19.8±3.5
Utilisation Level	Low	66	55.0%	16.2±1.3
	Medium	45	37.5%	20.4±1.4
	High	9	7.5%	26.2±1.8

Econometric Analysis: Determinants of Agro-Advisory Uptake

Multiple Linear Regression (OLS) and Binary Logistic Regression models were estimated to determine the socio-economic and perceptual drivers governing utilization scores and perceived need (Table 3).

The Ordinary Least Squares (OLS) model explained of the total variance in agro-advisory utilization ($R^2 = 0.584$, $F = 22.38$, $p < 0.001$).

1. Internet Access ($\beta = 3.942$, $p < 0.001$): Displayed the strongest positive impact on advisory utilization. Farmers with internet access scored, on average, 3.94 points higher on the adoption scale compared to non-connected peers.
2. Perceived Need ($\beta = 2.415$, $p < 0.001$): A strong positive predictor of utilization score, adding 2.42 points on average.
3. Education Level ($\beta = 0.481$, $p = 0.012$): Higher formal educational attainment significantly improved advisory utilization.
4. Annual Household Income ($\beta = 0.000012$, $p = 0.008$): Farmers with higher financial resources showed significantly higher advisory implementation.
5. Age ($\beta = -0.043$, $p = 0.028$): Exhibited a statistically significant negative coefficient, indicating that older farmers tend to utilize advisories less frequently than younger cohorts.
6. Gender and Family Size ($p > 0.10$): Did not exhibit statistically significant direct impacts on utilization scores after controlling for internet access, education, and income.

DISCUSSION

The empirical results from this study confirm that agro-advisory utilization in smallholder paddy production systems is governed by an interconnected set of digital infrastructure, individual perceptions,

Table 3: Econometric Model Estimates for Agro-Advisory Utilisation ($N=120$)

Predictor Variable	Unstandardized Coeff. (B)	Std. Error	Standardized Coeff. (β)	t-value	p-value
(Constant)	11.245	1.120	—	10.04	< 0.001***
Age	-0.043	0.019	-0.172	-2.26	0.028*
Gender	-0.210	0.415	-0.029	-0.51	0.611
Family Size	0.082	0.095	0.050	0.86	0.392
Education	0.481	0.188	0.201	2.56	0.012*
Annual Income	0.000012	0.000004	0.228	2.70	0.008**
Internet Access	3.942	0.482	0.512	8.18	< 0.001***
Perceived Need	2.415	0.510	0.298	4.74	< 0.001***

Note: Model Diagnostic Metrics: $R^2 = 0.584$; Adjusted $R^2 = 0.558$; $F(7,112) = 22.38$, $p < 0.001$. Statistical significance levels: *Significant at 5% level of significance, ** Significant at 1% level of significance, *** Significant at 0.1% level of significance.

and socio-economic capabilities. To contextualize these findings within the broader literature, this discussion synthesizes evidence from empirical studies across digital extension, climate-smart agriculture, and behavioral adoption models.

Digital Connectivity and the “Digital Divide”

Internet access emerged as the primary determinant governing advisory utilization ($B = 3.942, p < 0.001$). In their systematic review of digital extension frameworks, Amoussouhoui *et al.* (2024) emphasized that digital technology functions as a pivotal structural bridge, transforming raw data into actionable agronomic insights. Evaluating app-based advisory platforms in rice ecosystems, Amoussouhoui *et al.* (2023) confirmed that digital interventions significantly increase compliance with recommended farm schedules compared to conventional extension methods. Exploring mobile-based extension in South Asia, Mittal *et al.* (2020) demonstrated that customized digital advisories reduce information search costs and enhance input efficiency among smallholders. In a similar vein, Cole and Fernando (2021) found that mobile agricultural advice led to measurable improvements in practice change and overall crop yields.

Expanding on digital market channels, Abate *et al.* (2023) showed that digital extension services accelerate agricultural transformation by improving market participation. Xu *et al.* (2023) demonstrated that two-way interactive digital tools significantly enhance smallholder market performance and bargaining power. Highlighting scale benefits, Kansime *et al.* (2019) observed that digital extension models empower resource-constrained farmers by providing continuous access to expert knowledge. Furthermore, Akinboye *et al.* (2024) verified that digital systems enhance learning efficiency in rural communities. Evaluating grain production dynamics, Li *et al.* (2022) showed that cyber extension systems substantially improve farm decision-making quality.

Despite these clear benefits, Antwi-Agyei and Stringer (2021) cautioned that poor network connectivity and low digital literacy constrain smallholders from fully exploiting digital tools. Examining technical efficiency, Fadeyi *et al.* (2022) noted that digital literacy gaps directly limit the productivity benefits of agricultural software.

Addressing these constraints, Connor *et al.* (2021) advocated for “phygital” models that combine digital channels with local human extension networks. Furthermore, Rambod *et al.* (2023) and Waaswa *et al.* (2021) emphasized that continuous digital extension builds adaptive capacity, allowing farmers to respond dynamically to climate disruptions.

The Perception-Utilization “Know-Do” Gap

Although of farmers acknowledged needing advisory services, over 47% of these same individuals recorded low utilization scores (14–18). This discrepancy demonstrates that positive perception alone does not guarantee field-level adoption. In their comparative analysis of extension perceptions, Goodluck *et al.* (2024) identified a similar intent-action gap, noting that subjective recognition of advisory utility fails to translate into adoption without trust and institutional support. Analyzing institutional advisory trajectories, Labarthe and Laurent (2013) observed that modern advisory privatization often neglects the specific execution capabilities of smallholders.

Framing this within innovation adoption theories, Rogers (2003) and Leeuwis (2004) emphasized that perceived trialability, risk, and structural support dictate whether information leads to practice change. Klerkx *et al.* (2012) further argued that agricultural advisors must act as systemic innovation brokers to reduce perceived risk during initial technology trial phases. Birner *et al.* (2021) underscored that institutional governance and strong social networks are critical to amplifying the credibility and uptake of agricultural advice. In line with this, Kountios *et al.* (2022) confirmed that advisory service quality directly influences smart technology adoption rates.

Socio-economic Determinants: Age, Education, and Income

The negative coefficient for age ($B = -0.043, p = 0.028$) indicates that younger paddy cultivators are more receptive to integrating advisory recommendations into daily farm management. Younger farmers typically demonstrate higher digital self-efficacy and lower risk aversion, whereas older producers rely predominantly on traditional, generational farming practices.

Conversely, formal education ($B = 0.481, p = 0.012$) and annual household income ($B = 0.000012, p = 0.008$) exerted positive, statistically significant influences on advisory utilization. In their study using the Innovation Adoption Scale, Olum *et al.* (2019) demonstrated that formal education significantly enhances a farmer's cognitive readiness to transition from interest to actual technology adoption. Similarly, Gemedie and Jobir (2026) confirmed that capital constraints and input costs heavily dictate the intensity of technology adoption among smallholder farmers.

Evaluating agrometeorological services in rice-growing regions, Rohit *et al.* (2024) found that higher educational attainment directly correlates with better communication efficiency and advisory satisfaction. Nannewar *et al.* (2023) emphasized that higher income provides an essential financial buffer, enabling farmers to purchase recommended climate-resilient inputs and chemical treatments. In rainfed ecosystems, Dupdal *et al.* (2020) documented positive economic returns among farmers using structured agromet bulletins. Khan *et al.* (2018) verified that weather-based advisories significantly enhance farm income by optimizing chemical spray timings and fertilizer scheduling.

Assessing forecast credibility, Albizua *et al.* (2021) highlighted that trust and spatial accuracy are essential determinants of sustained advisory adoption. Empirical studies by Kumar *et al.* (2023), Harshini *et al.* (2023), and Doss and Asokhan (2024) consistently showed that addressing technical literacy gaps directly increases farmers' utilization of climate and weather advisory services.

Climate Resilience and Policy Implications

Integrating climate-smart agriculture (CSA) tools with advisory services yields vital environmental and yield benefits. Gemtou *et al.* (2025) and Oladele and Ngidi (2025) demonstrated that digital decision-support tools optimize resource allocation, thereby reducing input waste and greenhouse gas emissions. Msweli *et al.* (2024) and Willbroad *et al.* (2025) showed that real-time crop monitoring via IoT and satellite-driven advisories enhances drought resilience in smallholder rice fields. Addressing structural barriers, Olorunfemi *et al.* (2024) and Sithole *et al.* (2024) emphasized that supportive

policy frameworks and targeted credit access are critical to scaling digital extension tools in climate-vulnerable zones.

CONCLUSION

This empirical investigation provides critical insights into the socio-economic, perceptual, and technological drivers governing agro-advisory service uptake among paddy cultivators. By analyzing the data of 120 smallholder rice producers, the study reveals that while a significant majority of farmers (73.3%) perceive a clear need for agricultural advisories, actual field-level utilization remains predominantly low (55.0%). This highlights a pronounced "know-do gap" where favorable perceptions do not automatically translate into practice adoption due to underlying structural and resource constraints.

Econometric modeling demonstrates that *internet access* is the single most powerful catalyst for increasing advisory utilization ($B = 3.942, p < 0.001$), followed closely by favorable perceived need, higher formal education, and annual household income. Conversely, advancing age acts as a minor constraint, reflecting lower digital fluency and higher risk aversion among older farming cohorts.

Key Policy Recommendations & Future Directions

- ♦ *Developing Hybrid ("Phygital") Extension Systems:* Because of farmers currently lack functional internet connectivity, extension agencies must refrain from relying solely on smartphone applications or digital platforms. Instead, a dual delivery model—combining real-time digital/SMS alerts for connected farmers with localized, face-to-face contact for older and non-connected smallholders—is essential to prevent digital marginalization.
- ♦ *Targeting Educational & Demonstration Interventions:* Given the significant positive impact of education, advisory messages should be simplified into visual, interactive, and vernacular formats. Field demonstrations and local Farmer Producer Organization (FPO) networks should be leveraged to build trust

and demonstrate the clear economic return of recommended practices.

- ♦ *Aligning Advisory Content with Input Subsidies:* To bridge the intent-action gap among lower-income farmers, agro-advisories should be directly linked with local credit, seed, and fertilizer access programs, ensuring that farmers possess the financial capability to execute recommended farm practices.

LIMITATIONS AND FUTURE STUDIES

Based on the research paper provided, here are the key limitations of the study:

- (i) *Geographic & Sample Scope:* The study is based on a localized sample of 120 paddy cultivators (N=120). While this provides in-depth empirical insights into the specific ecosystem, the relatively small, geographically restricted sample limits the direct generalizability of the findings to broader regions or differing agro-ecological zones.
- (ii) *Cross-Sectional Data Design:* The research relies on a cross-sectional dataset collected at a single point in time. This design captures adoption and perception as static events rather than dynamic, evolving processes over time, making it difficult to establish firm long-term causal relationships.
- (iii) *Self-Reported Perceptual Data:* Measures of perceived need and practice utilization were captured via self-reported survey responses during structured interviews. This introduces potential recall bias or social desirability bias regarding how accurately farmers reported their actual field-level adoption rates.
- (iv) *Omission of Unobserved Institutional Factors:* While the econometric models account for key socio-demographic, economic, and digital predictors, certain institutional and environmental variables—such as proximity to local input markets, extension agent visit frequencies, credit accessibility, and specific climate shocks—were not explicitly modeled in the regression framework.

Directions for Future Studies:

- (i) *Expanded Longitudinal Tracking:* Future research could employ panel data across multiple crop cycles to observe how farmers' advisory utilization changes over time in response to seasonal weather variations, market price shifts, and ongoing digital literacy interventions.
- (ii) *Cross-Regional & Multi-Crop Comparisons:* Scaling the study to include larger sample sizes across diverse agricultural zones and different crop systems (e.g., wheat, maize, or commercial horticulture) would help test the robustness and generalizability of these econometric models.
- (iii) *Evaluating Mixed Interventions:* Given the strong impact of internet access alongside traditional barriers, future studies could experimentally evaluate hybrid “phygital” extension models (e.g., randomized controlled trials comparing digital-only, traditional-only, and combined extension interventions).

GENERATIVE AI DECLARATION

The author(s) confirm that there was no use of artificial intelligence (AI)-assisted technology for assisting in the writing or editing of the manuscript, and no images were manipulated using AI. The authors developed and verified all scientific content, data analysis, interpretation of results, and conclusions. The authors take full responsibility for the accuracy, integrity, and originality of the work presented, and no AI tool was listed as an author.

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