FARMER ADOPTION OF MOBILE AGRICULTURE APPLICATIONS: AN EMPIRICAL STUDY OF ADOPTION, USAGE AND AGRICULTURAL DECISION-MAKING

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***Abstract*—Mobile technologies have created new opportunities for delivering agricultural information and services directly to farmers. Mobile agriculture applications can provide weather information, market prices, crop advisory, pest and disease information, financial services, and decision-support. Previous studies have identified both the potential of these applications and barriers to their adoption, including digital literacy, connectivity, language, usability, trust, device access, and data costs. However, the reviewed literature largely treats application functionality, smartphone adoption, and the broader mAgriculture ecosystem as separate areas of study. This paper proposes an empirical framework for examining how farmer-level and application-level factors influence initial adoption, actual usage, and continued use of mobile agriculture applications, and whether such usage contributes to improved agricultural decision-making. The proposed study focuses on the Indian context and considers digital literacy, perceived usefulness, perceived ease of use, trust, information quality, local-language availability, and usability as major explanatory factors. A structured questionnaire and quantitative analysis are proposed, supported by a formal measurement model, regression specifications, and mediation tests. The paper does not report fabricated survey results; instead, it provides a research framework that can be implemented through primary data collection.**

***Keywords*—Mobile Agriculture, Farmer Adoption, Agricultural Applications, Digital Literacy, Technology Adoption, Continued Usage, Agricultural Decision-Making, mAgriculture.**

I. INTRODUCTION

Agriculture depends strongly on timely and reliable information. Farmers require information related to weather, crop management, market prices, pests and diseases, irrigation, fertilizers, financial services, and government schemes. Traditionally, this information has been accessed through agricultural extension workers, local experts, markets, fellow farmers, television, newspapers, and other communication channels. The expansion of smartphones and mobile connectivity has created an additional digital channel through which agricultural information can be delivered.

Mobile agriculture applications can provide farmers with weather forecasts, crop advice, market information, financial services, pest-management information, and other decision-support services. The reviewed 2023 literature describes applications such as Pusa Krishi, Kisan Suvidha, Farm-o-Pedia, and Meghdoot as examples of mobile solutions designed to support agricultural information and decision-making [1]. Earlier mAgriculture research also showed that mobile services can support several stages of the agricultural value chain, including market information, trade facilitation, financial services, agricultural support, and data collection [3].

However, availability does not necessarily lead to adoption or continued use. Farmers may face barriers related to digital literacy, network coverage, data costs, language, application complexity, trust, privacy, device access, and the perceived value of the information provided [1]. Therefore, understanding farmer adoption requires attention not only to whether an application exists, but also to why farmers choose to adopt, use, and continue using it.

II. PROBLEM STATEMENT

Despite the growing number of agricultural mobile applications, their practical value depends on farmers' willingness and ability to use them. A farmer may download an application but rarely use it, or may use it once and discontinue it. Thus, initial adoption, actual usage, and continued usage should be considered separate stages. The research problem addressed in this study is to determine which factors influence these stages and whether application usage is associated with better agricultural decision-making.

III. LITERATURE REVIEW

A. Mobile Applications for Agricultural Transformation

Saikanth et al. reviewed mobile applications for agricultural transformation and classified their uses around information, market opportunities, weather, crop management, financial management, and related services [1]. The review also identified digital divide, limited technology literacy, connectivity, data costs, usability, privacy, language, literacy, and sustainability as important challenges. It further emphasized awareness, training, perceived value, usability, trust, reliability, and device access as factors affecting adoption.

B. Smartphone Adoption Among Farmers

Michels et al. investigated smartphone adoption among 817 German farmers and examined the relationship between

adoption and farmer or farm characteristics [2]. Their study found that characteristics such as age, education, and farm size were associated with smartphone adoption. This work provides an empirical basis for understanding agricultural technology adoption, but its geographical context is Germany and its main focus is smartphone adoption rather than the complete pathway from adoption to continued use and decision-making.

IV. COMPARATIVE ANALYSIS OF EXISTING STUDIES

TABLE I: COMPARATIVE ANALYSIS OF EXISTING STUDIES

Study	Main focus	Gap relevant to present study
Saikanth et al. (2023) [1]	Mobile agricultural applications, benefits, challenges and recommendations.	Primarily a review; does not empirically test a unified adoption-to-outcome pathway.
Michels et al. (2020) [2]	Smartphone adoption among German farmers.	German context; mainly smartphone adoption rather than continued agricultural-app use.
Syngenta Foundation (2011) [3]	mAgriculture ecosystem, services and value-chain applications.	Older ecosystem-level view; does not test current farmer adoption and continued usage empirically.
Present study	Farmer adoption, actual usage, continued use and decision-making.	Proposes an integrated empirical framework in the Indian context.

V. RESEARCH GAP

The reviewed studies establish that mobile agricultural applications can provide weather information, market prices, agricultural advice, financial services, pest management, and decision-support, while also identifying barriers such as digital literacy, connectivity, language, usability, trust, device access, and data costs [1]. However, the studies have different primary purposes: Saikanth et al. provide a broad review of applications and their benefits, Michels et al. investigate smartphone adoption among German farmers, and the Syngenta Foundation report examines the broader mAgriculture ecosystem and service models [1]–[3].

A gap therefore remains in understanding how multiple factors collectively influence farmers' actual adoption and continued use of mobile agricultural applications, particularly in the Indian context, and whether regular use contributes to agricultural decision-making. The present study addresses this gap by connecting adoption factors → initial adoption → actual usage → continued usage → agricultural decision-making.

VI. RESEARCH OBJECTIVES

- To identify the major factors influencing farmers' adoption of mobile agriculture applications.
- To examine the influence of digital literacy on mobile agriculture application adoption.
- To examine the influence of perceived usefulness and perceived ease of use on adoption.
- To investigate the role of trust and information quality in adoption and continued usage.
- To examine whether local-language availability influences application usage.
- To analyze the relationship between actual application usage and continued usage intention.
- To examine whether continued application usage influences agricultural decision-making.
- To identify major barriers preventing effective use of agricultural applications.

VII. RESEARCH QUESTIONS

RQ1: What factors influence farmers' adoption of mobile agriculture applications?

RQ2: Does digital literacy influence adoption?

RQ3: Do perceived usefulness and ease of use influence adoption and continued use?

RQ4: Does trust in application information influence continued usage?

RQ5: Does local-language availability affect farmers' willingness to use agricultural applications?

RQ6: Does actual application usage influence agricultural decision-making?

VIII. HYPOTHESES

H1: Digital literacy positively influences adoption.

H2: Perceived usefulness positively influences adoption.

H3: Perceived ease of use positively influences adoption.

H4: Trust in agricultural application information positively influences adoption.

H5: Information quality positively influences continued usage.

H6: Local-language availability positively influences application usage.

H7: Actual application usage positively influences continued usage intention.

H8: Continued usage positively influences agricultural decision-making.

IX. CONCEPTUAL FRAMEWORK

The proposed framework integrates farmer-level characteristics and application-level perceptions with the stages of adoption and usage. The framework is designed to move beyond a simple adoption/no-adoption outcome and examine what happens after adoption:

Farmer Factors: (Age, Education, Digital Literacy, Farm Size) ⟶ Initial Adoption

Application Factors: (Usefulness, Ease of Use, Trust, Info Quality, Local Language) ⟶ Initial Adoption

Usage & Outcome Continuum: Initial Adoption ⟶ Actual Usage (Frequency, Purpose) ⟶ Continued Use (Intention) ⟶ Agricultural Decision-Making

X. VARIABLES OF THE STUDY

TABLE II: VARIABLES OF THE STUDY

Variable	Role	Examples / Measures
Digital literacy	Independent	Ability to use smartphone/app functions.
Perceived usefulness	Independent	Usefulness for farming decisions and information access.
Ease of use	Independent	Ease of learning and navigation.
Trust	Independent	Confidence in application information.
Information quality	Independent	Accuracy, relevance and reliability.
Local-language availability	Independent	Availability and understandability of regional-language content.
Adoption	Dependent / Mediator	Decision to use an agricultural application.
Actual usage	Mediator	Frequency and purpose of use.
Continued usage	Dependent / Mediator	Intention to continue using the application.
Decision-making	Outcome	Influence of app information on farming decisions.

XI. RESEARCH METHODOLOGY

A. Research Design

The study will use a quantitative empirical research design based on a structured questionnaire. The proposed design examines relationships among farmer characteristics, application characteristics, adoption, actual usage, continued usage, and agricultural decision-making.

B. Target Population

The target population will consist of farmers in India who use smartphones and have experience with, or exposure to, mobile agriculture applications. Applications may include weather, market-price, crop-advisory, pest and disease, government-service, financial, livestock, or agricultural marketplace applications.

C. Sampling

A target sample of approximately 200–400 farmers is proposed, subject to access and research resources. For a finite farmer population N (e.g., the farmers of the study district) and margin of error e, the minimum sample size is [4]:

$$n = N / (1 + N \cdot e^2) \tag{1}$$

When the population size is unknown, the sample size is computed from the confidence level z (1.96 for 95%) and the expected proportion p (0.5 when unknown) [4]:

$$n = z^2 \cdot p(1 - p) / e^2 \tag{2}$$

The final paper should report the actual sample obtained and should not replace missing responses with invented data.

D. Data Collection Instrument

A structured questionnaire will use a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree. The questionnaire will contain demographic items and multi-item measures for digital literacy, perceived usefulness, perceived ease of use, trust, information quality, local-language availability, adoption, actual usage, continued usage, and agricultural decision-making.

Each construct j is measured by k_j items. The score of farmer i on construct j is the mean of its items, where x_{ijq} is the response of farmer i to item q:

$$C_{ij} = (1/k_j) \cdot \Sigma_{q=1\ldots kj}\, x_{ijq} \tag{3}$$

To report scores on a 0–100 scale, the Digital Literacy Index (DLI) of farmer i is obtained from the digital-literacy construct score $C_{i,DL}$:

$$DLI_i = [(C_{i,DL} - 1) / 4] \times 100 \tag{4}$$

XII. PROPOSED DATA ANALYSIS

A. Descriptive Statistics

Descriptive statistics will summarize farmer demographics, application awareness, types of applications used, frequency of usage, and purposes of use. The adoption funnel is described by four rates, where n_{total} is the number of respondents, n_{adopt} the number who adopted an application, n_{active} the number who actively use it, and $n_{continue}$ the number who intend to continue:

$$AR = (n_{adopt} / n_{total}) \times 100 \tag{5}$$

$$UR = (n_{active} / n_{adopt}) \times 100 \tag{6}$$

$$RR = (n_{continue} / n_{active}) \times 100 \tag{7}$$

$$DR = 100 - RR \tag{8}$$

where AR is the adoption rate, UR the active usage rate, RR the retention rate, and DR the drop-off rate (all in %). Actual usage is summarized by the Usage Intensity Index (UI), which combines frequency (F), duration (D), and purpose diversity (P), each min–max normalized to [0, 1]:

$$UI_i = w_1\hat{F}_i + w_2\hat{D}_i + w_3\hat{P}_i \qquad w_k \geq 0,\ \Sigma w_k = 1 \tag{9}$$

$$\hat{x} = (x - x_{min}) / (x_{max} - x_{min}) \tag{10}$$

The Decision-Making Influence Index (DMI) is computed from the m decision-making items d_{iq} and then normalized to [0, 1]:

$$DMI_i = (1/m) \cdot \Sigma\, d_{iq} \qquad \hat{DMI}_i = (DMI_i - 1) / 4 \tag{11}$$

B. Reliability and Validity

Cronbach's alpha will be used to examine the internal consistency of multi-item constructs [5], where k is the number of items, σ^2_q the variance of item q, and σ^2_T the variance of the total score:

$$\alpha = [k / (k - 1)] \cdot [1 - \Sigma\sigma^2_q / \sigma^2_T] \tag{12}$$

A value of $\alpha \geq 0.70$ is considered acceptable. If PLS-SEM is used, composite reliability (CR) and average variance extracted (AVE) will be computed from the standardized loadings λ_q [6]:

$$CR = (\Sigma\lambda_q)^2 / [(\Sigma\lambda_q)^2 + \Sigma(1 - \lambda^2_q)] \tag{13}$$

$$AVE = \Sigma\lambda^2_q / k \tag{14}$$

Multicollinearity among predictors will be checked with the variance inflation factor, where R^2_j is obtained by regressing predictor j on all other predictors:

$$VIF_j = 1 / (1 - R^2_j) \tag{15}$$

C. Correlation Analysis

Pearson's correlation coefficient will be used to examine relationships among digital literacy, usefulness, ease of use, trust, information quality, adoption, continued usage, and decision-making, for any two constructs X and Y:

$$r = \Sigma(X_i - \bar{X})(Y_i - \bar{Y}) / \sqrt{[\Sigma(X_i - \bar{X})^2 \cdot \Sigma(Y_i - \bar{Y})^2]} \quad (16)$$

D. Regression Analysis

Regression analysis will identify significant predictors of adoption and continued usage. Because adoption is binary (A_i = 1 if farmer i adopted an application, otherwise 0), hypotheses H1–H4 are tested with logistic regression:

$$P(A_i = 1) = 1 / (1 + e^{-Li}) \quad (17)$$

$$L_i = \beta_0 + \beta_1 DL_i + \beta_2 PU_i + \beta_3 PEOU_i + \beta_4 TR_i + \beta_5 LL_i + \gamma' Z_i \quad (18)$$

where DL is digital literacy, PU perceived usefulness, PEOU ease of use, TR trust, LL local-language availability, and Z the control variables (age, education, farm size). The effect of each predictor is reported as an odds ratio:

$$OR_k = e^{\beta k} \quad (19)$$

Actual usage (H6), continued usage (H5, H7), and decision-making (H8) are modelled by linear regression, where IQ is information quality, UI the usage intensity index, CU continued usage, DMI the decision-making influence index, and ε_i the error term (the control-coefficient vector γ is estimated separately in each model):

$$UI_i = \alpha_0 + \alpha_1 LL_i + \alpha_2 PEOU_i + \alpha_3 DL_i + \gamma' Z_i + \varepsilon_i \quad (20)$$

$$CU_i = \delta_0 + \delta_1 IQ_i + \delta_2 UI_i + \delta_3 TR_i + \delta_4 PU_i + \gamma' Z_i + \varepsilon_i \quad (21)$$

$$DMI_i = \varphi_0 + \varphi_1 CU_i + \varphi_2 UI_i + \gamma' Z_i + \varepsilon_i \quad (22)$$

Model fit is assessed by adjusted R^2 (with n observations and p predictors) and the effect size of a predictor by Cohen's f^2, where R^2_{incl} and R^2_{excl} are the R^2 values with and without that predictor:

$$R^2_{adj} = 1 - (1 - R^2)(n - 1) / (n - p - 1) \quad (23)$$

$$f^2 = (R^2_{incl} - R^2_{excl}) / (1 - R^2_{incl}) \quad (24)$$

Each coefficient is tested against H_0: $\beta_k = 0$ at the 5% significance level, where SE is the standard error of the estimate:

$$t = \beta_k / SE(\beta_k) \quad (25)$$

Table III maps each hypothesis to its model and statistical test.

TABLE III: HYPOTHESIS-TO-MODEL MAP

Hypothesis	Model	Test
H1–H4 (adoption)	Eq. (17)–(18)	β significance; odds ratio, Eq. (19)
H5 (information quality → continued use)	Eq. (21)	t-test on δ_1
H6 (language → usage)	Eq. (20)	t-test on α_1
H7 (usage → continued use)	Eq. (21)	t-test on δ_2
H8 (continued use → decisions)	Eq. (22)	t-test on φ_1

E. Mediation Analysis

Because the framework treats usage and continued use as mediators, the indirect effect of an antecedent X on an outcome Y through a mediator M is the product of path a (X → M) and path b (M → Y) [7]. Its significance is tested with the Sobel statistic, and the total effect adds the direct effect c':

$$Indirect\ effect = a \times b \quad (26)$$

$$z = a \cdot b / \sqrt{(b^2 \cdot SE^2_a + a^2 \cdot SE^2_b)} \quad (27)$$

$$Total\ effect = c' + a \cdot b \quad (28)$$

F. Optional PLS-SEM

If the final sample size and research resources permit, PLS-SEM will be used to test the complete conceptual model and indirect relationships [8]. The structural model is:

$$\eta = B\eta + \Gamma\xi + \zeta \quad (29)$$

where η denotes the endogenous constructs (adoption, usage, continued use, decision-making), ξ the exogenous constructs (digital literacy, usefulness, ease of use, trust, information quality, language), B and Γ the path-coefficient matrices, and ζ the residual. Path significance is tested by bootstrapping (e.g., 5,000 resamples).

G. Barrier Severity Analysis

To address the barriers objective, the Relative Importance Index (RII) will rank each barrier (connectivity, data cost, language, trust, etc.), where W is the rating given by each respondent (1–5), A the highest rating (5), and N the total number of respondents. RII ranges from 0 to 1:

$$RII = \Sigma W / (A \times N) \quad (30)$$

H. Group Differences

Associations between categorical variables (e.g., adoption and education level) will be tested with the chi-square statistic, where O and E are the observed and expected frequencies. Differences in usage across small, medium, and large farmers will be tested with one-way ANOVA:

$$\chi^2 = \Sigma (O - E)^2 / E \quad (31)$$

$$F = MS_{between} / MS_{within} \quad (32)$$

XIII. QUESTIONNAIRE DIMENSIONS

Demographic profile: Age, education, farming experience, farm size, location, smartphone ownership.

Digital literacy: Ability and confidence in using smartphones and applications.

Perceived usefulness: Whether the application helps access useful information and improve decisions.

Ease of use: Ease of learning, navigation and feature use.

Trust: Confidence in the accuracy and reliability of app information.

Information quality: Accuracy, relevance, timeliness and clarity.

Local language: Availability and understandability of regional-language content.

Actual usage: Frequency, duration and purpose of application use.

Continued use: Intention to keep using and recommend the application.

Decision-making: Whether application information influences farming activities and choices.

XIV. EXPECTED CONTRIBUTION

A. Academic contribution: The study proposes an integrated framework that connects farmer characteristics and application characteristics with adoption, actual usage, continued usage, and agricultural decision-making, and operationalizes it through a formal measurement and analysis model. This extends research that treats smartphone adoption, application functionality, and agricultural benefits as separate issues.

B. Practical contribution: Findings from the completed survey can help application developers identify which features or barriers are most strongly associated with adoption and continued use. For example, evidence about language, usability, trust, or information quality could guide application design.

C. Policy contribution: Agricultural departments and extension organizations may use the findings to improve digital-literacy programs, farmer awareness, regional-language support, and digital agricultural services.

XV. EXPECTED FINDINGS

The literature suggests that perceived usefulness, digital literacy, ease of use, trust, information quality, and local relevance may influence adoption and continued usage [1], [2]. It is also reasonable to investigate whether farmers who use applications more frequently report greater influence of application-based information on agricultural decisions. These statements are expectations for the proposed empirical study, not reported findings. Actual statistical results must be calculated from the collected survey data.

XVI. LIMITATIONS

- The study may use a geographically limited sample depending on access to farmers.
- Self-reported responses may introduce response bias.
- Farmers without smartphone access may be underrepresented.
- A cross-sectional survey cannot establish strong causal relationships over time.
- Actual yield and income outcomes may be difficult to measure accurately using self-reported data.
- Different agricultural applications may vary substantially in quality and functionality.
- Regional differences in language, farming practices, connectivity, and digital literacy may affect adoption.

XVII. FUTURE SCOPE

- Longitudinal studies across multiple agricultural seasons.
- Comparison of farmers across different Indian states and regions.
- Separate analysis of small, medium, and large farmers.
- Evaluation of regional-language agricultural applications.
- Integration of AI-based agricultural advisory systems.
- Integration of real-time weather, IoT, crop and market data.
- Study of information accuracy, trust, privacy and security.
- Measurement of actual agricultural productivity and economic outcomes.

XVIII. CONCLUSION

Mobile agriculture applications provide an important digital channel for delivering agricultural information and services. The reviewed literature demonstrates their potential in weather forecasting, market information, crop management, financial services, pest management, and agricultural advisory services. At the same time, adoption can be affected by digital literacy, usability, trust, language, connectivity, device access, information quality, and perceived usefulness [1].

The key gap is that adoption should not be treated as the final outcome. A farmer may download an application without using it regularly, and regular usage does not automatically demonstrate that the information influences farming decisions. Therefore, this study proposes an empirical framework, with a formal measurement model and analysis plan, connecting adoption factors, initial adoption, actual usage, continued usage, and agricultural decision-making in the Indian context. The proposed research can provide evidence that is useful for researchers, developers, agricultural extension organizations, and policymakers.

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