# Factors Influencing the Adoption of IoT Based Micro Level Farm Intelligence Systems by Dryland Farmers in the State of Andhra Pradesh

T. Yamini[1], Y. Prabhavathi[1,*] and Vani Srilatha[2]
[1]*Institute of Agribusiness Management, S V Agril College, Acharya N G Ranga Agricultural University, Tirupati, India*
[2]*Agricultural Extension, DAATTC, Acharya N G Ranga Agricultural University, Lam, Guntur, India*

Keywords: Smart Agriculture, IoT, Micro Level Crop Intelligence Systems, Binary Logit.

Abstract: Small holders in India are faced with multiple challenges, with limited access to essential information being a prominent hurdle, hindering their ability in making informed decisions throughout the crop cycle. This leaves them to various risks, particularly weather and pest attacks. Application of smart agricultural technological innovations such as AI, IoT, big data, robots, and drones enhances decision support systems, farm efficiency with promising economic and social benefits for smallholders, yet adoption remains a significant challenge in Indian agricultural landscape. Hence, the study majorly emphasizes on identifying the determinants of adoption of IoT (Internet of Things) based micro level crop intelligence systems in Anantapur district of Andhra Pradesh state, a region highly susceptible to climate changes. Primary data from a sample of 100 and employing binary logistic regression revealed that factors namely perceived usefulness, perceived ease of use, farmer innovativeness, facilitating factors and influential factors significantly increased the likelihood of adoption of IoT technologies. Conversely, perceived cost and complexity of decision making for farm operations decreased the likelihood of adoption. Thus the study advocates boosting adoption factors and streamlining processes to integrate IoT in smallholder farming, enhancing resilience and farm efficiency amidst challenges.

## 1 INTRODUCTION

Indian farmers, predominantly small holders, grappled with challenges encompassing land fragmentation, resource constraints and market volatility. Access to right information throughout crop cycle remains a significant challenge. Despite relying on their own knowledge, advices from fellow farmers, input dealers and institutional sources for farm decisions, farmers still confront with risks of weather and pest attacks (Rehman, et al. 2013; Kapur and Kumar, 2015). Technological innovations in agriculture are identified as potential solutions for challenges in Indian agriculture. Smart agriculture integrates IoT, drones, big data and AI into precision farming, enabling real-time data on soil moisture, weather and crop water needs. This optimizes fertilization, pest control and irrigation leading increased productivity. This aligns with Sustainable Development Goals, offering substantial economic, social, and environmental benefits (FAO, 2019). IoT optimizes dryland farming with weather tracking, crop monitoring and smart irrigation, cutting yield losses and financial risk.

While IoT offers benefits to smallholder farmers, its widespread adoption across India remains a significant challenge, with slow adoption rates by farmers globally (Walter et al. 2017). Slow adoption rates persist due to lack of technical proficiency and socio-demographic and other factors among farmers. Reliable internet connectivity is essential access to access real-time information, but costly. Further, time gap between the technology and its adoption at farmer level is driven by these drivers and hence farmers showing unwillingness to shift from conventional practices (Naik et al. 2022). understanding these determinants is crucial for promoting adoption of

* Corresponding Author



Yamini, T., Prabhavathi, Y. and Srilatha, V.
Factors Influencing the Adoption of IoT Based Micro Level Farm Intelligence Systems by Dryland Farmers in the State of Andhra Pradesh.
DOI: 10.5220/0012882000004519

In *Proceedings of the 1st International Conference on Emerging Innovations for Sustainable Agriculture (ICEISA 2024)*, pages 69-77
ISBN: 978-989-758-714-6

these technologies as they holds immense potential for revolutionizing the agricultural through efficient decision support systems. Hence, the study aims to identify factors influencing farmers adoption of various farm level crop intelligence systems in Anantapur District of Andhra Pradesh.

# 2 LITERATURE REVIEW

The present study adds to the growing body of literature by identifying factors influencing the adoption of IoT based farm intelligence systems. Adrian et al. (2005) identified that perception of usefulness, perception of ease of use, attitude of confidence, perception of net benefit, farm size and farmer educational levels positively influenced the farmers intention in adoption of precision agriculture technologies (PAT). Souza Filho et al. (2011) emphasized socio-economic, crop, land ownership, technology and systemic factors along with neighboring farmers, institutions, and social norms influenced PAT adoption. According to Tey and Brindal (2012), factors influencing PAT adoption include socio economic, institutional, behavioural, agroecological, information sources, farmers perception, technology and farmers behavior. Aubert et al. (2012) emphasized that Perceived ease of use, usefulness, resource availability, trialability, and farmer characteristics impact PAT adoption, while farm size does not.

Antolini et al. (2015) highlighted that socio-economic, agro-ecological, institutional, technological and behavioural factors, information sources and farmers perception were key adoption drivers of PAT. Tubtiang and Pipatpanuvittaya (2015) revealed guava farmers' adoption of smart farm technologies is influenced not only by perceived usefulness and ease of use but also by external factors like financing and land structure. Torrez et al. (2016) identified farm size, operator size, cropping efficiency, risk aversion, and time are key factors influencing PAT adoption among Kansas farmers, with large farms and operator age showed linear and inverse relationships. As per Paustian and Theuvsen, (2017), among various socio demographic factors, networking events significantly influenced Denmark and German farmers’ adoption of PAT.

Chuang et al. (2020) found that organizational support, income, trust, perceived usefulness and ease of use positively drives young farmers' intention to adopt IoT technologies, while factors like land ownership and willingness-to-pay had affected these decisions. While insufficient information, knowledge, awareness and perceived practical value hinders adoption. Vecchio et al. (2020) examined that higher rates of adoption of PAT were among younger, highly educated farmers with access to intensive information and large farm sizes holders. Yatribi (2020) emphasized that perceived utility remains the most identified determinant while farmers gender and experience were not always determinants for adoption. According to Mohr and Rainer Kuhl (2021), perceived behavioural control had the greatest influence followed by farmers personal attitude in acceptance of Artificial intelligence systems in agriculture. Rosario et al**.** (2022) employing structural equation model revealed that socio-psychological determinants play a key role in understanding the decision making process in the context of adoption of sustainable agriculture innovations.

# 3 MATERIALS AND METHODS

## 3.1 Selection of Study Area and Sample Respondents

Anantapur district of Andhra Pradesh, the second driest district in India, was chosen for its vulnerability to climate change and with more than 70 % of farmers depending on agricultural agriculture (MANAGE, 2019). Recent trends showed that dryland farmers of the district are shifting from annual to perennial crops to mitigate climate risks. NGOs, agri-tech startups like FASAL, FYLLO and government institutions are promoting farming services centered around IoT-based farm-level crop intelligence systems in the study area. Adoption of these technologies in these climate susceptible areas has wider scope of impacting the agriculture towards attaining sustainability through facilitating farmers to take informed decisions at every stage of crop cycle. The study obtained a list of farmers adopting IoT-based crop intelligence technologies from agri-tech startups and randomly selected 50 farmers. Additionally, 50 neighboring farmers with similar irrigation, cropping, and market conditions were identified, making the sample size to 100 farmers.

## 3.2 Description of Interview Schedule

The interview schedule for primary data collection comprised two main components. The first addressed socio demographic and other information particulars to identify the determinants. The second component included 33 statements rated on a five-point Likert scale and these statements covered perceived usefulness, ease of use, decision-making complexity, predictive abilities, resource scarcity, produce quality, farmer innovativeness, influential and facilitating factors, and perceived cost components.

Perceived usefulness was measured by facilitating timely decisions, resource optimization, yield increase, operation monitoring, and risk mitigation. Perceived ease of use assessed simplicity in acquisition, operation, and maintenance. Decision-making complexity considered technology suitability, climate vulnerability, and operational compatibility. Predictive decision-making assessed technology for predictive farm operations and climate risk mitigation. Resource scarcity evaluated technology for areas with Farmer innovativeness was gauged by proactive technology search, interest in operations, willingness to experiment, and risk acceptance. Influential factors included recommendations from peers, departments, media, and social platforms. Perceived cost assessed initial and recurring expenses versus benefits.

## 3.3 Statistical Techniques Employed for the Study

### 3.3.1 Binary Logistic Regression

The functional form of binary regression (logistic) model is briefly described as follows:

$$Ln\ [Pi1\text{-}Pi] = \beta0 + \beta1X1 + \beta2X2 + \beta3X3 + \beta4X4 + \beta5X5 + \beta6X6 + \beta7X7 + \beta8X8 + \beta9X9 + \beta10X10 + \beta11X11 + \beta12X12 + \beta13X13 + \beta14X14 + \beta15X15 + \beta16X16 + \beta17X17 + \beta18X18 + \beta19X19 + \beta20X20$$

Where, Pi is the probability that the farmer adopted farm level crop intelligence systems, that takes value of 1, if adopted and 0 otherwise

$Xi$ is a vector of the independent variables hypothesized to influence the adoption decision and these variables are Table 1 revealed that majority of the sample farmers were in the age group of 30-45 years (47 %) had education level of degree and above (55 %), had family size between four to six (68 %), had more than 15 years of farming experience (46 &) and were large farmers (53 %) with land holdings of more than 10 acres.

| | |
|---|---|
| X1 – Age (Categorical, with less than 30 years as reference over others | X11 – Perceived Usefulness |
| X2 – Education (Continuous variable) | X12 – Perceived Ease of Use |
| X3 – Farming Experience (Continuous variable) | X13 – Complexity of decision making |
| X4 – Farm size (Continuous variable) | X14 – Predictive Decision making |
| X5 – Membership in farmer collectives (1 for Yes, 0, otherwise) | X15 – Resource Scarcity |
| X6 – Leadership role (1 for Yes, 0, otherwise) | X16 – Farm Produce Quality |
| X7 – Attending farm related events (Not attending as reference over Others) | X17 – Farmer Innovativeness |
| X8 – Usage of agricultural technological apps (1 for Yes, 0, otherwise | X18 – Influential Factors |
| X9 – Mass media for agri information. (Newspaper as reference over radio & television) | X19 – Facilitating Factors |
| X10 – Social media for agri information (You Tube as reference over WhatsApp, Facebook) | X20 – Perceived Cost |

# 4 RESULTS AND DISCUSSION

## 4.1 Descriptive Statistics

Table 1: Socio-demographic characteristics of sample farmers.

| S. No | Age | Frequency | Percentage (%) |
|---|---|---|---|
| Age | Less than 30 years | 15 | 15 |
| | 30 - 45 years | **47** | **47** |
| | 45 - 60 years | 36 | 36 |
| | More than 60 years | 2 | 2 |
| Educational Level | Primary Education | 7 | 7 |

| | | | |
|---|---|---|---|
| | Secondary Education | 30 | 30 |
| | Intermediate | 8 | 8 |
| | Degree and above | **55** | **55** |
| Family Size | 1 to 3 | 24 | 24 |
| | 4 to 6 | **68** | **68** |
| | 7 to 9 | 0 | 0 |
| | 10 & above | 8 | 8 |
| Farming Experience | 1 to 5 years | 24 | 24 |
| | 6 to 10 years | 27 | 27 |
| | 11 to 15 years | 3 | 3 |
| | >15 years | **46** | **46** |
| Farm Size | < 2.5 Acres (Marginal farmer) | 0 | 0 |
| | 2.5 to 5 Acres (Small farmers) | 18 | 18 |
| | 5 to 10 Acres (Medium farmers) | 29 | 29 |
| | >10 Acres (Large farmers) | **53** | **53** |

## 4.2 Other Profile Characteristics of Sample Respondents

Table 2 results indicated that 56% of surveyed farmers seldom participated in agricultural events of state departments, NGOs or financial institutions. Only 10% were members of farmer collectives and 8% held leadership roles. About 34% had prior experience with agricultural technology. Television (82%) was the primary mass media source, followed by newspapers (18%). Facebook (66%) and YouTube (34%) were the main social media platforms for agricultural information.

## 4.3 Determinants of Adoption of Farm Level Crop Intelligence Systems by Farmers (First Set of Factors)

Binary logistic regression employed to identify first set of factors (Tables 4.1 & 4.2) influencing farmers adoption of farm level crop intelligence systems. The dependent variable is categorical and dichotomous i.e., it takes the value of 1 for sample farmers

Table 2: Other profile characteristics of Sample Respondents.

| S. No | Age | Frequency | Percentage (%) |
|---|---|---|---|
| Farmers Participation in Farm Related Events | Nil | 23 | 23 |
| | Rarely | 56 | 56 |
| | Regularly | 21 | 21 |
| Membership in farmer collectives (FPOs) | Yes | 10 | 10 |
| | No | 90 | 90 |
| Leadership role played in community | Yes | 8 | 8 |
| | No | 92 | 92 |
| Agriculture Related Technological application usage | Yes | 34 | 34 |
| | No | 66 | 66 |
| Mass media platforms as source of agricultural information | Newspaper | 18 | 18 |
| | Radio | 0 | 0 |
| | TV | **82** | **82** |
| Social media platforms as source of agricultural information | YouTube | 34 | 34 |
| | WhatsApp | 0 | 0 |
| | Facebook | **66** | **66** |

Table 3 : Results of Binary Logistic Regression (First Set of factors).

**Omnibus Tests of Model Coefficients**

| | | Chi-square | df | Sig. |
|---|---|---|---|---|
| Step 1 | Step | 68.730 | 14 | .000 |
| | Block | 68.730 | 14 | .000 |
| | Model | 68.730 | 14 | .000 |

**Model Summary**

| Step | -2 Log likelihood | Cox & Snell R Square | Nagelkerke R Square |
|---|---|---|---|
| 1 | 69.900[a] | .497 | .663 |

**Hosmer and Lemeshow Test**

| Step | Chi-square | df | Sig. |
|---|---|---|---|
| 1 | 52.003 | 8 | .000 |

**Classification Table[a]**

| | Observed | | Predicted | | |
|---|---|---|---|---|---|
| | | | FLCIS ADOP | | Percentage Correct |
| | | | NO | YES | |
| Step 1 | FLCIS ADOP | NO | 46 | 4 | 92.0 |
| | | YES | 5 | 45 | 90.0 |
| | Overall Percentage | | | | 91.0 |

a. The cut value is .500

**Variables in the Equation**

| | | B | S.E. | Wald | df | Sig. | Exp(B) | 95%C.I.for EXP(B) | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | Lower | Upper |
| Step 1[a] | AGEGRP | | | 12.097 | 3 | **.007*** | | | |
| | AGEGRP (1) | -28.669 | 28385.35 | .000 | 1 | .999 | .000 | .000 | . |
| | AGEGRP (2) | -23.670 | 28385.35 | .000 | 1 | .999 | .000 | .000 | . |
| | AGEGRP (3) | -21.722 | 28385.35 | .000 | 1 | .999 | .000 | .000 | . |
| | EDU | .486 | .185 | 6.878 | 1 | **.009*** | 1.625 | 1.131 | 2.336 |
| | FARMEXP | -.144 | .052 | 7.566 | 1 | **.006***** | .866 | .781 | .959 |
| | FARMSIZE | .242 | .057 | 17.846 | 1 | **.000***** | 1.274 | 1.139 | 1.425 |
| | MEMSHIP (1) | 3.534 | 1.863 | 3.600 | 1 | **.050**** | 34.262 | .890 | 1318.805 |
| | LEADSHIP (1) | 1.251 | 2.295 | .297 | 1 | .586 | 3.494 | .039 | 314.110 |
| | AFRE | | | 5.451 | 2 | **.066*** | | | |
| | AFRE (1) | -3.099 | 1.344 | 5.319 | 1 | **.021**** | .045 | .003 | .628 |
| | AFRE (2) | -1.921 | 1.153 | 2.774 | 1 | **.096*** | .146 | .015 | 1.404 |
| | ARTP (1) | 2.278 | .964 | 5.584 | 1 | **.018**** | 9.761 | 1.475 | 64.593 |
| | MMP (1) | 1.592 | 1.332 | 1.429 | 1 | .232 | 4.913 | .361 | 66.818 |
| | SMPF (1) | .397 | 1.048 | .143 | 1 | .705 | 1.487 | .191 | 11.597 |
| | Constant | 11.216 | 28385.355 | .000 | 1 | 1.000 | 74310.131 | | |

a. Variable(s) entered on step 1: AGEGRP, EDU, FARMEXP, FARMSIZE, MEMSHIP, LEADSHIP, AFRE, ARTP, MMP, SMPF.

*** indicates 1% ; ** indicates 5 %; * indicates 10 % Significance level who adopted farm level crop intelligence systems and 0 otherwise. Independent variables include age, education, farming experience, farm size, membership, leadership, participation in farm events, usage of agricultural apps, mass media and social media for agricultural information. represented with codes AGEGRP, EDU, FARMEXP, FARMSIZE, MEMSHIP, LEADSHIP, ARTP, MMP and SMPF respectively

The results of logit model (Table 3) showed the model is good fit and statistically significant, as the probability is less than 0.05 with chi square ($\chi^2$) value of 52.003. The Nagelkerke R Square value explains 66.30 % of variance while classification table indicated that the model correctly classified 91 % of cases. The variables namely age, education, farming experience, farm size, membership in farmer collectives, participation in farm events/meeting and usage of agricultural apps are key determinants influencing farmers adoption of farm level crop intelligence systems. Of these determinants, education farm size, membership, and previous experience with agricultural technological apps increases the likelihood of adoption.The findings are consistent with the results of Diaz et al., (2021) and Hoang (2020) also established the positive relationship for education and farm size with technology adoption by farmers. Further participation in farmer collective organizations facilitates the exchange of information regarding the benefits of technology adoption, which increases the probability of adoption.

While the variables namely age, farming experience and participation of farmers in farm events decreases the likelihood of adoption. Farmers in the age group of 18 to 30 years, showed increased likelihood of adoption over other categories i.ewith increase in age and farming experience, the farmers will be less technology savvy. Further there might be negative feedbacks and criticism of technology during farmers participation in farm related meetings/events, which might be the factor for decreased adoption. The results are consistent with findings of Daberkow and McBride (2003); Adrian et al. (2005); Torrez et al. (2016) and Vecchio et al. (2020).

## 4.4 Reliability Results of Data Set

The statements identified for assessment of adoption of farm level crop level intelligence systems showed internal consistency and reliability with Cronbach's alpha value above 0.70 (Cronbach and Shavelson, 2004; Table 4).

## 4.5 Determinants of Adoption of Farm Level Crop Intelligence Systems (Second Set of Factors)

Binary logistic regression was further employed to identify second set of factors influencing the farmers adoption of farm level crop intelligence systems. Scores for each statement were determined based on scale agreements, then summed to calculate total scores for each factor. The total scores of independent variables for the components perceived usefulness, perceived ease of use, complex decision making, predictive decision-making, resource scarcity, produce quality, farmer innovativeness, influential factor, facilitating factor and perceived cost are represented with PUTS, PEOUTS, CDMTS, PDMTS, RSTS, PQTS, FARMINVTTS, INFFACTTS, FACTS, PCTS respectively.

Table 4. Results of reliability of data set.

| **Factors** | **No. of statements** | Cronbach's Alpha Value |
|---|---|---|
| Perceived usefulness | 5 | 0.953 |
| Perceived ease of use | 4 | 0.919 |
| Complex decision making | 3 | 0.727 |
| Predictive decision making | 2 | 0.839 |
| Resource scarcity | 3 | 0.827 |
| Farm produce quality | 2 | 0.728 |
| Farmer innovativeness | 4 | 0.817 |
| Influential factors | 4 | 0.898 |
| Facilitating factors | 3 | 0.811 |
| Perceived cost | 3 | 0.718 |
| **Total** | **33** | |

Table 5. Results of Binary Logistic Regression (Second Set of factors).

| **Omnibus Tests of Model Coefficients** | | | | |
|---|---|---|---|---|
| | | Chi-square | df | Sig. |
| Step 1 | Step | 61.831 | 10 | .000 |
| | Block | 61.831 | 10 | .000 |
| | Model | 61.831 | 10 | .000 |

| **Model Summary** | | | |
|---|---|---|---|
| Step | -2 Log likelihood | Cox & Snell R Square | Nagelkerke R Square |
| 1 | 76.798[a] | .461 | .615 |

| **Hosmer and Lemeshow Test** | | | |
|---|---|---|---|
| Step | Chi-square | df | Sig. |
| 1 | 13.023 | 8 | .111 |

| **Classification Table[a]** | | | | | |
|---|---|---|---|---|---|
| | Observed | | Predicted | | |
| | | | FLCIS ADOP | | Percentage Correct |
| | | | NO | YES | |
| Step 1 | FLCIS ADOP | NO | 40 | 10 | 80.0 |
| | | YES | 7 | 43 | 86.0 |
| | Overall Percentage | | | | 83.0 |
| a. The cut value is .500 | | | | | |

| **Variables in the Equation** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | B | S.E. | Wald | df | Sig. | Exp(B) | 95% C.I.for EXP(B) | |
| | | | | | | | | Lower | Upper |
| Step 1[a] | PUTS | .839 | .246 | 11.618 | 1 | **.001*****| 2.313 | 1.428 | 3.747 |
| | PEOUTS | .617 | .227 | 7.406 | 1 | **.007***** | 1.854 | 1.189 | 2.893 |
| | CDMTS | -.668 | .374 | 3.201 | 1 | **.074*** | .513 | .246 | 1.066 |
| | PDMTS | -.039 | .276 | .020 | 1 | .889 | .962 | .560 | 1.654 |
| | RSTS | -.089 | .279 | .101 | 1 | .751 | .915 | .529 | 1.582 |
| | PQTS | -.006 | .364 | .000 | 1 | .986 | .994 | .487 | 2.029 |
| | FARMINVTTS | .917 | .396 | 5.368 | 1 | **.021**** | 2.501 | 1.152 | 5.431 |
| | INFFACTTS | .518 | .244 | 4.525 | 1 | **.033**** | 1.679 | 1.042 | 2.708 |
| | FACTS | .906 | .354 | 6.566 | 1 | **.010**** | 2.474 | 1.237 | 4.948 |
| | PCTS | -.726 | .295 | 6.078 | 1 | **.014**** | .484 | .272 | .862 |
| | Constant | -42.618 | 13.106 | 10.574 | 1 | .001 | .000 | | |

a. Variable(s) entered on step 1: PUTS, PEOUTS, CDMTS, PDMTS, RSTS, PQTS, FARMINVTTS, INFFACTTS, FACTS, PCTS.
b. *** indicates 1% ; ** indicates 5 %; * indicates 10 % Significance level

The results of logit model (Table 4) showed model is good fit and statistically significant, as the probability is less than 0.05 with chi square (χ^2) value of 13.023. The Nagelkerke R Square value indicated that model explained 61.50 % of variance and correctly classified 83 % of the cases. The key determinants include perceived usefulness, perceived ease of use, farmer innovativeness, facilitating factors, influential factors, increases the likelihood of adoption of these systems, while perceived cost and complexity of decision making decreases the likelihood of adoption.

Sample farmers who perceive crop intelligence systems as facilitating timely decision-making, resource utilization, yield enhancement, and risk mitigation are more inclined to adopt them. Likewise, those who find these systems easy to acquire, operate, understand, and maintain are also likely to adopt. Farmers who actively seek technological information, experiment with new technologies, and accept associated risks are more inclined towards adoption. Moreover, those who trust recommendations from fellow farmers, agricultural departments, media sources, and social media are more likely to adopt. Perceived support from service providers, government subsidies, and financial aid, as well as bank linkages, also increase adoption likelihood. Conversely, farmers who find initial costs and ongoing expenses unjustifiable, or perceive systems as suitable only for specific crops and climates, are less likely to adopt. The findings align with results of Antolini et al. (2015); Chuang et al. (2020) and Diaz et al.(2021) supporting similar results.

## 5 CONCLUSION

The study aims to identify determinants of farm-level crop intelligence system adoption among 100 dryland farmers in climate-vulnerable Anantapur District, Andhra Pradesh, where making the adoption of these technologies is crucial for enabling informed decision-making across the crop cycle. Binary logistic regression revealed age, education, farming experience, farm size, collective membership, farmer participation in farm events, and app usage as crucial determinants while age, experience, and participation in farm events decreases the adoption likelihood. Additionally, perceived usefulness, ease of use, farmer innovativeness, decision complexity, facilitating factors, influential recommendations, and perceived costs significantly influenced the adoption.

Understanding these determinants is essential for fostering the adoption of these systems. Tailored strategies addressing adoption drivers, showcasing benefits, user-friendliness and cost-effectiveness, enabling support structures while addressing connectivity and financial constraints are crucial. Collaborative efforts among stakeholders, including NGOs, agricultural departments and agri-tech startups, are vital for promoting technology adoption and sustainable agricultural practices in climate-vulnerable regions like Anantapur.

## AUTHOR CONTRIBUTIONS

| **Author Position** | **Name of the Author** | **Authors Contribution** |
|---|---|---|
| First Author | T Yamini | Data Collection, Data Validation, Data Analysis, Original Draft Preparation, |
| Corresponding Author | Y Prabhavathi | Conceptualization, Study Design, Data Analysis, Original Draft Preparation, Draft Correction |
| Co-Author | Ch Srilatha Vani | Draft correction |

**Funding:** This research received no external funding.

**Conflicts of Interest:** The authors declare no conflict of interest

## REFERENCES


Aubert, B. A., Schroeder, A.,&Grimaudo J. (2012). IT as enabler of sustainable farming: An empirical analysis of farmers' adoption decision of precision agriculture technology. *Decision Support Systems*, 54, 510–520.

Adrian A.M., Norwood, S.H., & Mask, P.L. (2005). Producers' perceptions and attitudes toward precision agriculture technologies. *Computers and Electronics in Agriculture*, 48(3), 256-271.

Antolini, L.S., Scare, R.F., & Dias, A. (2015). Adoption of precision agriculture technologies by farmers: A systematic literature review and proposition of an integrated conceptual framework. *International Food and Agribusiness Management Association* (*IFAMA*) *World Conference,* June 14. 14-17.

Chuang, J.H., Wang, J.H., & Liang, C. (2020). Implementation of Internet of Things depends on intention: Young farmers' willingness to accept innovative technology. *International Food and Agribusiness Management Review,* 23(2): 253-266.

Cronbach L.J., & Shavelson R. J. (2004). My Current Thoughts on Coefficient Alpha and Successor Procedures. *Educational and Psychological Measurement*, 64(3), 391–418

Daberkow, S.G., & McBride, W.D. (2003). Information and the adoption of precision farming technologies. *Journal of Agricultural and Applied Economics,* 21(1), 21-38.

FAO. (2019). Sustainable Development Goals, Food and Agricultural Organization, United Nations. https://www.fao.org/3/CA3121EN/ca3121en.pdf

Kapoor, S., & Kumar, N. (2015). Use and contribution of information sources in buying process of agri-inputs by farmers in India. *Journal of Agriculture and Food Information*, 16, 134-150

MANAGE. (2019). Extension Advisory Services for Climate Smart Agriculture. A Case of Anantapur District, Andhra Pradesh, India. Discussion Paper 1, MANAGE – Centre for Climate Change And Adaptation, Hyderabad.https://www.manage.gov.in/publications/discussion%20papers/MANAGE-CCA-Discussion%20Paper.pdf

Mohr, S., & Kühl, R. (2021). Acceptance of artificial intelligence in German agriculture: an application of the technology acceptance model and the theory of planned behavior. *Precision Agriculture*, 22(6), 1816-1844

Naik, B.M., Singh, A.K and Maji, S. (2022). Constraints in Adoption of Climate Resilient Agricultural Technologies in Telangana. *Indian Journal of Extension Education*, 58(4), 163-165

Paustian, M., & Theuvsen, L. (2017). Adoption of precision agriculture technologies by German crop farmers. *Precision agriculture,*18 (5), 701-716.

Rehman, F., Muhammad, S., Ashraf, I., Mahmood Ch., K., Ruby, T., & Bibi, I. (2013). Effect of farmers' socioeconomic characteristics on access to agricultural information: Empirical evidence from Pakistan. *The Journal of Animal and Plant Sciences*, 23(1), 324–329.

Rosário, J., Madureira, L., Marques, C., & Silva, R. 2022. Understanding Farmer's Adoption of Sustainable Agriculture Innovations: A Systematic Literature Review. *Agronomy,* 12(11), 2879.

Souza Filho, H. M., Buainain, A. M., Silveira, J. M. F. J., Vinholis, M. M. B. (2011). Constraints in the adoption of Technological innovation in Agriculture. *Cadernos De Ciencia and Technologia,* 1(28): 223-255.

Tamirat, T.W., Pedersen, S.M., & Lind, K.M. (2018). Farm and Operator Characteristics affecting adoption of precision agriculture in Denmark and Germany. *Acta Agriculturae Scandinavica, Section B Soil and Plant Science,* 68(4), 349-357.

Tey, Y. S.; Brindal, M. (2012). Factors influencing the adoption of precision agricultural technologies: a review for policy implications. *Precision Agriculture*, 13:713–30.

Torrez, C., Miller, N., Ramsey, S., & Griffin, T. (2016). Factors Influencing the Adoption of Precision Agriculture Technologies by Kansas Farmers. Department of Agricultural Economics, Extension Publication Kensas State University.

Tubtiang, A., &Pipatpanuvittaya, S. (2015). A study of factors that affect attitude toward deploying smart-farm technologies in Tanud subdistrict, DamnoenSaduak district in Ratchaburi province. *Journal of Food Science and Agricultural Technology*, 1, 144-148.

Vecchio, Y., Agnusdei, G.P., Miglietta, P.P., & Capitanio, F. (2020). Adoption of precision farming tools: The case of Italian farmers. *International Journal of Environmental Research and Public Health*, 17(3), 869.

Walter, A., Finger, R., Huber, R., Buchmann, N. (2017). Smart farming is key to developing sustainable agriculture. Proceedings of the National Academy of Sciences USA, 114 (24), 6148-6150