Farmer Perceptions and Economic Significance of Kissan Drones in Maize Production: An Empirical Field Study

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ABSTRACT: Agriculture remains the backbone of India's economy, with maize ranking third among food crops, contributing 9% to the national food basket and over ₹100 billion to agricultural GDP. The integration of Agriculture 5.0 technologies artificial intelligence, drone technology, and the Internet of Things plays a pivotal role in addressing agricultural challenges and enhancing sustainability. This study explores farmer perceptions and the economic implications of Kissan Drone adoption in maize production, focusing on intensive cultivation areas in Tamil Nadu. Using advanced statistical models, the research evaluates adoption levels, willingness to pay, and economic feasibility, providing data-driven policy recommendations. Demographic analysis reveals a generational technology gap, with adopters averaging 42 years, potential adopters 52 years, and non-adopters 64 years. Findings indicate that drone adoption for Fall Armyworm (FAW) control reduces spraying costs by 22%. Regression analysis suggests that tailored educational programs can enhance adoption rates, but pricing alignment and innovative dissemination strategies remain crucial. The study concludes with policy recommendations to accelerate Kissan Drone adoption and promote sustainable farming practice.

1 INTRODUCTION

Agriculture is the main source of income for about two thirds of India's population, and it makes a substantial contribution to the GDP of the country (Ministry of Finance, 2022). In order to solve current issues and advance sustainability, digital technology must completely revolutionise agriculture. Emerging technologies like artificial intelligence, drone technology, and internet of things play pivotal roles in enhancing agricultural production and creating more predictable, sustainable, and seamless supply chains. Drone technology has brought remarkable precision and efficiency to farming practices, revolutionizing tasks such as pesticide and liquid fertilizer applications, water area mapping, water sampling, pest infestation tracking, and crop management. Recognizing these advantages and market potential, the Indian government introduced "Kisan drones" to address operational delays, reduce pesticide and fertilizer consumption through automation, lower spraying and fertilizer application costs, and minimize human exposure to hazardous chemicals. To ensure inclusive adoption, it is essential to formulate a strategy that achieves economies of scale in Kisan drones, making them accessible to all types of farmers. This research aims to explore Kisan drone technology adoption and its economic impact at the farm level. Ultimately, this policy framework aims to improve the precision and efficiency of agricultural practices, thereby contributing to the sustainable development of Indian agriculture.

2 REVIEW OF LITERATURE

Drones revolutionize modern agriculture by enabling precision crop monitoring, resource optimization, and cost reduction (Ahirwar et al., 2019); Beriya, 2022). Yet, widespread adoption faces hurdles like regulatory constraints and the need for extensive training. Despite its potential, research on drone technology in Indian agriculture is limited, with farmers' perceptions and adoption influenced by their technological familiarity and education levels. (Puri et al., 2017); (Dutta and Goswami, 2020). Studies suggest that larger farms with greater resources tend to adopt drone technology more rapidly, benefiting from their

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enhanced capacity to absorb initial investment costs (Kelley et al., 2003). However, the adoption rate of drones in agriculture remains modest, accounting for only 3% of the farming community. This tepid adoption is attributed to barriers such as upfront costs and limited access to training and technical support. Despite these challenges, drones offer compelling economic benefits. Research indicates that 95% of farmers in Ghana were willing to pay for drone technology due to its potential to enhance crop yields, reduce input costs, and improve resource allocation (Annor-Frempong and Akaba, 2020); Techno-economic feasibility assessments have revealed favorable returns on investment, with notable internal rates of return and significant increases in farmers' revenue and time savings per hectare (Mogili and Deepak, 2018). Farmers' adoption decisions are complex and influenced by personal, contextual, and operational factors. While some farmers may remain unaware of the benefits of drone technology, others perceive drones as overly intricate or disruptive to their traditional farming methodologies (Suvedi et al., 2022). Thus, addressing these barriers and tailoring adoption strategies to farmers' diverse needs and contexts are crucial for accelerating the uptake of drone technology in agriculture.

3 RESEARCH GAP

The literature on Kisan drone technology in agriculture has predominantly focused on farmers' perceptions, adoption rates, and economic outcomes, particularly in maize cultivation. However, a significant research gap exists regarding the comprehensive exploration of perceptions and economies of drone adoption in India. Addressing this gap is essential as it can offer insights into drones' actual economic benefits, affecting farmers' income, cost reduction, and resource optimization. Existing studies, primarily from developed nations, lack thorough research on economic implications. Bridging this gap could foster a more holistic understanding of Kisan drones' role in Indian agriculture, guiding policy decisions and promoting sustainable practices.

4 RESEARCH QUESTIONS

The existing research concerning Kisan drone technology has predominantly centered on examining farmers' perceptions, adoption rates, and the resulting economic consequences within the context of maize cultivation. Nevertheless, there exists a noticeable dearth of comprehensive studies dedicated to the economic aspects of drone technology. The following research explore the key factors influencing farmers' perceptions regarding the adoption and their willingness to pay for this technology adoption.

5 OBJECTIVES OF THE STUDY

This study comprehensively explores Kisan drone technology adoption and its agricultural impact, with interconnected objectives. It seeks to understand farmers' perceptions, dynamics of Kisan drone adoption, and estimate willingness to pay using direct inquiry method. Additionally, it evaluates the economics of drone application, empowering farmers to optimize resource utilization. Finally, the study advocates for policy options encouraging responsible and widespread drone use, aiming to bridge gaps between perception, economics, and policy for informed decision-making and sustainable practices.

6 METHODOLOGY OF THE STUDY

The research endeavours to examine comprehensively the perceptions of farmers, the dynamics governing awareness and adoption, their willingness to pay, and the cost economics associated with the utilization of Kisan drone technology, particularly within the realm of maize cultivation in Tamil Nadu. The selection of maize as the focal crop stems from its heightened susceptibility to pests and reliance on plant protection chemicals, rendering it conducive to the integration of drones into the production process. The research methodology entails a cross-sectional survey approach using validated questionnaire to survey the respondents in way of direct interviews.

Sampling Technique

A multi-stage random sampling technique is used to select 240 maize farmers from the Dindigul and Tirupur districts. Farmers are categorized into three groups: adopters (actively using Kissan Drones), potential adopters (interested but not yet using), and non-adopters (not interested).

The districts serve as separate strata to ensure balanced representation. The total sample is divided proportionally based on the maize farming population in each district. Within each district, specific blocks with maize cultivation are randomly selected.
This approach ensures a representative and diverse sample of maize farmers.

Modelling Adoption

The FACOPA model was adopted to analyse factors influencing adoption, considering socio-structural factors and perceived complexities. Multinomial logit analysis will be used to understand varying levels of propensity to adopt. Principal Component Analysis (PCA) will be used to reduce the dimensionality of the dataset, particularly concerning perceived complexities related to Kisan drone adoption. This will help identify key factors influencing adoption perceptions. Linear regression was adopted to explore the relationship between socio-structural variables and the perception of complexity, using the principal components as dependent variables and other socio-economic and farm-related variables as independent variables. The estimated willingness to pay and assess cost economics for drone technology through direct inquiry methods with respondents, providing valuable insights into the economic aspects of adoption.

7 RESULTS AND DISCUSSION

7.1 Distribution of Respondents' Socioeconomic Characteristics

Socioeconomic characteristics encompass a range of attributes and factors that delineate the economic and social standing of individuals, households, communities, or broader populations. These characteristics offer valuable insights into the distribution of assets, opportunities, and access to services within a society. The respondents were categorized based on their perceptions of drone use in crop production. The classification includes adopters, who actively employ or express positive interest in drone technology (N=94); individuals with an idea for adoption, indicating interest but no active commitment (N=61); and those not willing to adopt, who show reluctance or disinterest in drone use (N=85). This classification facilitates a significant understanding of attitudes toward drones in agriculture, capturing varying levels of acceptance and apprehension within the surveyed population. The examination of the table reveals distinct variations in the average age of respondents across the three identified categories. Notably, the average age within the adopter's category is relatively younger, standing at 42 years. In contrast, individuals indicating an idea for adoption exhibit an average age of 52 years, while those expressing a lack of willingness to adopt Kissan drones have an average age of 64 years. This disparity underscores a clear pattern wherein younger farmers show a greater propensity to embrace Kissan drones. It is evident that respondents in the younger age demographic exhibit a more favourable perception towards Kissan drone adoption compared to their older counterparts, suggesting a generational divide in the acceptance of this technology within the agricultural community.

Table 1: Socio Economic characteristics of surveyed respondents.

Variables	Adopters (N=92)	Willing to Adopt (N=61)	Not Willing to Adopt (N=85)	Total (N=240)
Age in Years (Mean)	47	52	64	54
Education				
Collegiate level	57	8	10	75
Higher Secondary	34	31	16	81
Secondary level	3	18	34	55
Primary level	0	4	17	21
No formal Education	0	0	8	8
Intensity in farm operations				
Less than 50 days per year	12	14	17	43
Between 50 to 100 days per year	18	41	38	97
Between 101 to 150 days per year	29	5	24	58
More than 50 days	35	1	6	42
Information Pursuing				
Less than 5 hours per month	15	20	31	66
Between 5 to 10 hours per month	12	23	17	52

Between 10 to 15 hours per month	38	12	18	68
More than 15 hours per month	29	6	19	54
Size of Farm in ha (Mean)	3.68	3.15	3.32	3.38

7.2 Frequency Adoption of Kissan Drone

The control of Maize Fall Armyworm using Kissan drones represents a groundbreaking and innovative approach that holds significant promise for farmers. The study contributes fresh perspectives by shedding light on the frequency interval of Kissan drone usage in Maize Fall Armyworm control. Analyzing the frequency of Kissan drone adoption offers valuable insights into the integration of this technology into agricultural practices. The inform strategies aimed at promoting wider acceptance and utilization of drone technology among farmers, ultimately fostering more sustainable and productive farming practices. The data clearly indicates that adopters primarily utilize drones for spraying insecticide against the Fall Armyworm (FAW). Among adopters, approximately 58.5 percent employ Kissan drones for this purpose twice during the maize production cycle, followed by 27.7 percent who use them only once. A smaller percentage, approximately 10.6 percent of the surveyed respondents, utilizes drones thrice during the maize production cycle. These findings underscore the prevalence of drone usage among adopters and highlight the frequency with which they integrate this technology into their maize production practices, particularly for combating FAW infestations.

Table 2: Frequency and purpose of adoption.

Frequency interval	Purpose of Adoption	(N=94)
Only once	Spraying insecticide against FAW	26 (27.7)
Two times	Spraying insecticide against FAW	55 (58.5)
Three times	Spraying insecticide against FAW	10 (10.6)
Three and above	Spraying insecticide against FAW	3(3.2)

7.3 Factors–Complexity Perception Adoption of Kissan Drones in Agriculture

To explore the influence of perceived complexity on drone adoption, a survey was carried out among maize cultivating farmers. The surveys were conducted in a face-to-face manner, and the respondents self-completed a paper questionnaire with the support of a researcher. The aim of the analysis is to measure the probability of PA adoption as dependent on perceived complexity, which is established as a composite variable. Therefore, a purposive sample technique was used. A questionnaire was submitted to a sample of 300 farmers. This sampling technique aims to subjectively select interviewees with the purpose of gathering detailed information on the object of study (Kelley et al. 2003). To obtain a purposive sample, an initial question was asked: "Have you ever heard of precision agriculture?" If the answer was negative, the respondents were excluded from the survey. This choice was due to the desire to have a sample that was at least "aware" of the subject of the survey. To exploratory work, purposive sampling is commonly used to collect empirical data (Etikan et al. 2016). The complexity perceived from adopting drone technologies is gauged using six distinct factors, each assessed on a Likert scale from 1 (strongly disagree) to 5 (strongly agree), to demonstrate their potential impact on adoption. These factors include:

Cost Impact (co): The deployment of Agriculture 5.0 technologies contributes to farm efficiency by lowering operational costs.

Management Complexity (mo): The implementation of these technologies introduces complexities in farm management, necessitating enhanced managerial competencies.

Organizational Adjustment (oo): Adopting these technologies may pose challenges in organizational and structural adaptation.

Agricultural Practice Modification (po): Drone technologies necessitate alterations to traditional farming practices.

Financial Commitment (fo): The investment in these technologies involves substantial financial outlays that may be difficult to recoup.

Adoption Rarity (io): The prevalence of Agriculture 5.0 technologies is limited in the regions where farmers are operating.

To examine the relationship among variables within the same conceptual framework, an initial correlation analysis was employed. This analysis revealed significant relationships among the six factors, as evidenced by noteworthy Pearson correlation coefficients ($p < 0.01$) detailed in Table 3 Following the identification of these significant correlations, we assessed the internal consistency of the dataset using Cronbach's alpha, a metric that evaluates the reliability of a scale by determining the cohesion among a set of items. While a high Cronbach's alpha value doesn't confirm the one-dimensionality of a scale, it prompted us to further investigate this aspect through exploratory factor analysis. Consequently, these variables were chosen for Principal Component Analysis (PCA), which identified a single component accounting for 68% of the total variance. This component's extraction validates the interconnectedness among various dimensions and enables us to refine our understanding of complexity through a unified indicator derived from the PCA coefficients. With this index established, the analysis can proceed in two stages.

A linear regression model is employed to examine the impact of socio-structural factors on the complexity perception. By applying this analytical approach, we can pinpoint which factors play a crucial role in shaping an individual's perception throughout the adoption phase. Prior to conducting the linear regression, a correlation analysis was carried out to ensure that there was no correlation among the socio-structural variables. The analysis reveals that the socio-structural variables exhibit weak correlations with each other, all values falling below 0.6. This suggests a limited association between the variables, indicating that changes in one variable are not strongly linked to changes in another.

Table 3: Correlation analysis for the perceived complexity.

Factors	CI	MC	OA	APM	FC	AR
CI	1					
MC	0.471**	1				
OA	0.279*	0.571*	1			
APM	0.376**	0.608**	0.509**	1		
FC	0.573*	0.189*	0.411**	0.397**	1	
AR	0.543*	0.411**	0.365*	0.456**	0.272**	1

*Note: ** indicates 1% level of significance, * indicates 5% level of significance.*

Table 4: Matrix components of principal component analysis.

Matrix components	Average factor loadings
Cost Impact	0.712
Management Complexity	0.591
Organizational Adjustment	0.671
Agricultural Practice Modification	0.817
Financial Commitment	0.756
Adoption Rarity	0.627

The multiple linear regression analysis elucidates how various socio-structural factors influence farmers' perceptions of complexity regarding the perception of new agricultural technology i.e., drone. The analysis delineates a nuanced landscape where each factor—age, education, landholding size, intensity of work, and information intensity—plays a distinct role in shaping these perceptions. At the outset, the analysis reveals an inverse relationship between age and perceived complexity. Specifically, older farmers tend to view the adoption of new technologies as less complex, suggesting that experience or familiarity with farming practices may mitigate concerns over integrating new technologies (Pannell et al., 2006). This finding highlights a potential generational divide in the adoption process, where younger farmers might perceive greater barriers to technology integration, possibly due to less experience or different attitudes towards innovation (Ntshangase et al., 2018). Education emerges as a factor that positively related with perceived complexity. This suggests that more educated farmers, who are presumably more aware of the potential challenges and benefits of new technologies, perceive greater complexity in adopting these innovations. This counterintuitive finding might reflect a more critical evaluation of new technologies by educated farmers, underscoring the need for educational programs to address not only the benefits but also the practical challenges of technology adoption (Kumar et. al., 2020). The size of landholding also positively influences perceived complexity, indicating that farmers with larger operations perceive greater challenges in adopting new technologies. This could be attributed to the logistical and managerial complexities associated with implementing new technologies on a larger scale. Thus, support mechanisms for technology adoption may need to be scalable and adaptable to the size of the farming operation (Rejeb et al., 2022).

Conversely, the intensity of work and information intensity exhibit negative correlations with perceived complexity. Farmers who are more engaged in their work and those who dedicate more time to acquiring information through various channels tend to perceive lower complexity in adopting new technologies. These findings highlight the importance of active engagement and information access in facilitating technology adoption. Specifically, they suggest that initiatives aimed at increasing farmers' exposure to information and knowledge about new technologies could play a critical role in reducing perceived barriers and complexities (Babu et al., 2012)/

Table 5: Correlates of socio-structural factors.

Factors	Age	Education	Landholding	Intensity of work	Intensity of information
Age	1				
Education	-0.271	1			
Landholding (ha)	0.479	0.409	1		
Intensity of work	-0.287	0.189	-0.573	1	
Intensity of information	0.499	0.618	0.476	0.258	1

In sum, the regression analysis provides critical insights for policymakers and practitioners aiming to foster agricultural technology adoption. Tailoring support and educational programs to address the specific needs and perceptions of different farmer groups—considering factors such as age, education level, landholding size, and information-seeking behavior could enhance the adoption rates of new agricultural technologies. These insights underscore the necessity of a nuanced approach to technology dissemination and adoption support, one that acknowledges the diverse landscape of the agricultural sector and the varied perceptions of farmers towards new technology.

7.4 Actual Pay and Willingness to Pay for Kissan Drone

The adopters were specifically approached to provide valuable insights into two pivotal aspects above the actual payments made by farmers for the utilization of the Kissan drone and their willingness to pay for its usage. The detailed insights serve to inform analysis and strategic decision-making in agricultural technology adoption initiatives, contributing to more informed and effective practices in the field.

The figure reveals that adopters perceive their current payment for drone per spray to be higher than their willingness to pay. According to consumer surplus theory, the actual payment should ideally be lower than the willingness to pay to ensure societal welfare. However, these findings raise concerns that the cost of drone spray might need to be reduced to encourage continuous adoption. This discrepancy suggests a potential barrier to sustained adoption of drone spray technology and underscores the importance of aligning pricing strategies with adopters' expectations and economic realities. Adjusting the cost structure could help enhance the affordability and accessibility of drone spray services, thereby fostering broader adoption and maximizing societal benefits in agricultural practices.

Table 7: Cost Comparison of *Kissan* drone spray and other spray methods.

Particulars	Kissan drone Adopters (94)	Non adopters (61+85=146)
Average Spraying cost per ha	1776	2355
Purchase cost of chemicals	985	1205
Total cost of crop protection	2761	3560
Per cent of cost reduction	22 percent	

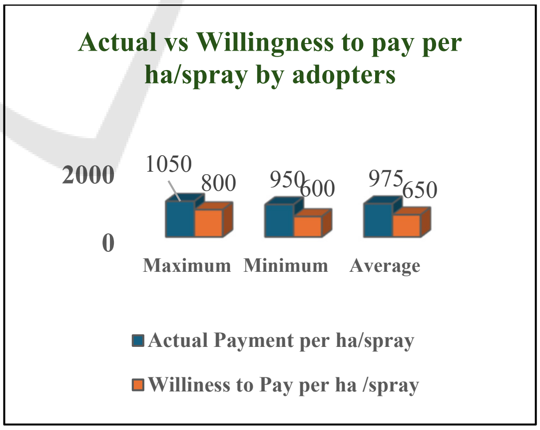

Figure 1: Actual pay Vs willingness to pay in adoption (N=94).

Based on the responses gathered from the respondents, it was observed that there was a tangible 22 percent reduction in the cost of spraying, translating to an absolute difference of 799 units. However, this reduction was deemed inadequate as an optimal cost-saving measure. To effectively leverage technology intervention and substantially bolster farm profits, a cost reduction exceeding 50 percent is imperative.

8 CONCLUSION

The research concerning Kisan drone technology that distinct variations in the average age of respondents across the three categories. Adopters have an average age of 42 years, while individuals considering adoption average 52 years, and those unwilling to adopt have an average age of 64 years. This age disparity indicates that younger farmers are more inclined to embrace Kissan drones, highlighting a generational gap in technology acceptance within the agricultural community. The study explore that adopters primarily use drones for spraying insecticide against Fall Armyworm (FAW). The findings derived from the regression analysis indicate that mediatisation and educational programs to supply to the unique needs and perceptions of diverse farmer groups while bearing in mind factors such as age, education level, landholding size, and information-seeking behavior has the potential to significantly enhance adoption rates. The emphasis lies in adopting a innovative approach to technology dissemination and adoption support that recognizes the complex landscape of the agricultural sector and acknowledges the diverse perspectives held by farmers regarding new technology. The study also insight that adopters perceive current drone spray costs to exceed their willingness to pay, contrary to consumer surplus theory. Positioning pricing strategies with adopters' expectations and economic realities is crucial to foster broader adoption and maximize societal benefits in agriculture. Respondents noted a 22% reduction in spraying costs, equating to 799 units, yet deemed inadequate for optimal savings. Further cost reductions are needed to leverage technology for substantial farm profit enhancement. Based on the findings outlined in the research, several policy suggestions can be proposed to address the challenges and opportunities identified in Kisan drone adoption and its impact on agriculture

1) Develop tailored support programs aimed at different farmer groups based on their adoption behaviour (adopters, potential adopters, and non-adopters). These programs should address specific needs and perceptions identified in the study, considering factors such as age, education level, and farm size.

2) Enhance financial assistance schemes for drone purchases and field demonstrations, particularly targeting lower-income farmer groups. This could include subsidies, grants, or low-interest loans to make drone technology more accessible.

3) Implement comprehensive education and training programs to increase awareness and improve understanding of drone technology and its benefits among farmers. These programs should focus on practical aspects of drone operation, maintenance, and integration into existing farming practices

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