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Impact of drone technology on agriculture - farmers' perception analysis

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Abstract

Unmanned aerial vehicles (UAVs), or drones, are revolutionizing agricultural practices by enhancing precision and efficiency in crop management. This study examines the impact of drone technology on agriculture in Coimbatore district, Tamil Nadu, focusing on farmers' perceptions and the extent of drone adoption. Covering a sample size of 120 farmers, the research explores various aspects of drone usage, including its benefits and challenges. Key advantages include reduced chemical usage, improved crop monitoring, precise irrigation, increased yields and water conservation. Government initiatives like the Kisan Drone program support the adoption of agricultural drones through subsidies and financial aid. However, high initial costs, technical complexity and regulatory barriers limit widespread adoption, particularly among small and marginal farmers. Custom hiring centres and enhanced government support are identified as potential solutions. Statistical methods such as binary logistic regression, propensity score matching and factor analysis are used to analyze adoption patterns and barriers. Findings reveal that drone spraying is the most common application, with higher awareness and adoption rates among educated farmers. The study concludes with recommendations to improve accessibility, reduce costs and expand training programs to benefit farmers across all socioeconomic segments.

Keywords

agriculture; farmer perception; precision farming; technology adoption; UAV

Introduction

Indian agriculture sector gambles with several challenges, like typical monsoons, production-related issues, low productivity, labour shortages, price changes, etc., despite accounting for 20.2% of the countrys' GDP (1). Drones are changing traditional agriculture by improving efficiency and enabling precision farming. They are used for spraying pesticides, soil analysis, irrigation control and crop health evaluation (2). Drones can revolutionize Indian agriculture by providing data-driven insights, enhancing productivity, reducing labour costs and promoting sustainable farming practices (3). However, farmers' adoption of drone technology differs significantly in developing countries where access to advanced technologies is sometimes restricted (4). Farmers are aware of agricultural drones through social media, conventional media and word-of-mouth, but their adoption is hampered due to financial, technological and legal constraints (5). Custom hiring centres in India offer drone rental services, making them more accessible and affordable for small and marginal farmers (5).

Globally, drones have emerged as critical tools in sustainable agriculture. In the United States, supportive regulatory frameworks such as the FAAs' Part 107 rule have fostered their adoption, enabling practices like precision spraying and real-time crop monitoring, which result in higher yields and resource efficiency. Similarly, China leads in agricultural drone usage due to its cost-effective manufacturing and government incentives, with widespread applications in pesticide spraying. However, cost, operator training and regulatory barriers persist worldwide.

European nations like France, Germany and the Netherlands increasingly use drones to promote sustainable farming practices, supported by harmonized regulations from the European Union Aviation Safety Agency (EASA). These practices often integrate privacy considerations to address societal concerns. In countries like Australia and New Zealand, drones are invaluable for managing large, remote farms and conserving water resources, which is critical for sustainable agriculture in water-scarce regions. Developing regions in Africa and South America also exhibit the potential for drone usage in agriculture, addressing traditional inefficiencies and climate resilience. Initiatives like the Technical Centre for Agricultural and Rural Cooperations' drone piloting projects in Uganda and emerging regulations in Brazil and Argentina pave the way for broader adoption.

The usage of drones in agriculture is greatly influenced by farm size, Credit availability, agricultural practices and the perceived advantages of higher productivity, labour efficiency and water savings (6). Small farmers face challenges because of drones' high initial and maintenance costs (7). There are still other technical barriers, like specialized training to operate drones, the impact of weather on drone operation and the short battery life of UAVs (8). This study aims to understand farmers' awareness of agricultural drone technology, usage trends and challenges. It also evaluates the advantages of farming drones, covering improved crop health, efficient spraying, reduced labour and increased yields (9).

The studys' objective includes understanding the extent of drone application and key factors influencing farmers' intentions to use drones in agriculture operations. To identify the specific constraints and barriers hindering the usage of drone technology in agriculture and the suitable strategies for overcoming the constraints.

Materials and Methods

Tamil Nadu is one of the leading states in India in terms of agricultural innovation and the adoption of new technologies. Coimbatore district, known as the Manchester of South India, is renowned for its agricultural research and development activities. With its diverse cropping patterns and progressive farming community, the Coimbatore district stands out as an ideal location for studying the impact of an innovative interaction like drone technology in agriculture. The districts' prominent agricultural activities and significant use of drone technology in farming practices justify their selection. Coimbatore is known for its innovative farm landscape and farmers' enthusiastic adoption of modern farming techniques. This openness to new solutions and active involvement in various agricultural activities provide a rich context for researching the impact of drone technology in agriculture. Therefore, the Coimbatore district was purposively chosen for this study. This study involved 120 respondents, a sample size chosen to ensure statistical power and precision for the planned analyses, including binary logistic regression, propensity score matching, chi-square tests and Garrett ranking. This size balances practical constraints such as resource availability with methodological needs, allowing robust estimation and reliable insights while reducing potential bias. The sample respondents were chosen from various villages within the district, ensuring a diverse representation of farming practices. Villages were randomly selected from blocks such as Karamadai, Madukkarai, Kinathukadavu, Sulur, Sultanpettai, Periyanayakkanpalayam, Annur, Coimbatore North, Thondamuthur, Anamalai and Mettupalayam. Primary data were collected through structured interviews with pre-prepared questionnaires focusing on farmers' perceptions and experiences with agricultural drone technology.

Binary logistic regression

The binary logistic regression was employed in this study to measure the adoption level of drone technology among small and marginal farmers. This statistical method models the relationship between a binary dependent variable and one or more independent variables. For binary logistic regression, the dependent variable is awareness about drones and the independent variable is crop type, education, farm size and income level.

Where,

P is the probability of the event (adoption of drone technology).

β_o is the intercept.

β_1, β_2…β (k) are the coefficients of the independent variables.

X_1, X_2, …X_ k are the independent variables (demographic factors).

The logistic regression model estimates the coefficients, which indicate the strength and direction of the relationship between each independent variable and the likelihood of adopting drone technology.

Propensity score matching

To compare the results of farmers who adopted drone technology and those who did not, Propensity Score Matching (PSM) was used. PSM is a statistical method that pairs groups according to variables before comparing their results to minimize selection bias. The propensity score matching formula is as follows in Equation 1.

$$\widehat{(P_i)} = \frac{e^{loglog\left(\frac{p}{1-p}\right)}}{1+e^{loglog\left(\frac{p}{1-p}\right)}} \quad \text{Eqn. 1}$$

PSM provides valuable insights by minimizing bias and allowing for a more accurate comparison of outcomes between adopters and non-adopters of drone technology.

Likerts' scale technique

The Likert scale is a psychological statistical tool for analyzing customer values, opinions and attitudes. In this study, a five-point scale is used to allow consumers to indicate how strongly they agree or disagree with a given statement.

Factor Analysis

Factor analysis was used in this study to identify and group the various factors that influence the farmers' intention to use drones. The different aspects are Operational Efficiency (efficiency of spraying, reduced time, labour efficiency, water saving, convenience), Productivity and Yield (crop yield, disease detection), Economic Feasibility (credit access, cost-effectiveness), Adoption Drivers (farm size, weather conditions) and Regulatory Considerations (legal regulations). The different factors were recorded on a Likert scale.

Garretts' Ranking Technique

Garretts' ranking method was employed to determine the obstacles in drone usage in agriculture. Garretts' ranking technique was used to transform the sample respondents' order of merit into scores. Using this method, a sample of respondents ranked each element and the rankings were then converted into a score value using the formula mentioned in Equation 2.

Percent position = 100 *(Rij – 0.5)/Nj×100 Eqn. 2.

Table 1. Demographic characteristics

Demographic factors	Number of farmers	Percentage
Gender		
Male	116	96.67
Female	4	3.33
Age		
25-34 years	17	14.17
35-44 years	53	44.17
45-54 years	38	31.67
55-64 years	12	10
Level of Education		
Illiterate	2	1.67
Primary	14	11.67
Secondary	62	51.67
Graduate	40	33.33
Postgraduate	2	1.67
Family type		
Nuclear	68	56.67
Joint	52	43.33
Size of farm		
Marginal	24	20
Small	30	25
Medium	44	36.67
Large	22	18.33
Income level		
Less than 1 lakhs	21	17.50
1-5 lakhs	47	39.17
5-10 lakhs	35	29.17
More than 10 lakhs	17	14.16
Awareness		
Aware	88	73.33
Unaware	32	26.67
Adoption		
Adopters	74	61.67
Non-adopters	46	38.33

Results and Discussion

Demographic characteristics

The demographic characteristics of the sample respondents revealed that most farmers were male (96.67%). Age distribution of sample respondents showed that most farmers are in the age group of 35-44 years (44.17%), followed by 45-54 years (31.67%), indicating a predominance of middle-aged farmers. The level of education among sample respondents reveals that most of the farmers have completed secondary education (51.67%), while 33.33% had graduated. This suggests that the farmers in the study area were well-educated, with a considerable proportion having access to higher education. Concerning family structure, 56.67% of the farmers are from nuclear families, while 43.33% were from joint families. Farm size data indicates that 36.67% were medium-sized, followed by 25% small and 20% marginal farms, with only 18.33% large farms. The sample farmers' income level is mostly 1-5 lakhs (39.17%), followed by 5-10 lakhs (29.17%). When it came to awareness of drone technology, 73.33% of farmers were aware of its application. Among those aware, 61.67% had adopted drone technology for their agricultural practices.

Binary logistic regression

Binary logistic regression was used to find the association of factors such as gender, education, farm size and income level with the awareness of drones in agriculture. To ensure robustness and reliability, the models' validity was assessed using standard fit statistics, including the Hosmer-Lemeshow goodness-of-fit test and Nagelkerkes' R^2.

Fig. 1. shows data on the awareness of drone technology among a sample of 120 respondents. The survey reveals a positive outlook on drone adoption, with a significant majority (73.33%) indicating awareness of this technology. This suggests a potential openness to incorporating drones into agricultural practices. However, a minority (26.6%) remains unaware of drone technology, highlighting the need for targeted outreach efforts to educate farmers about the potential benefits of drones in agriculture. Farmers are aware of agricultural drones through social media, conventional media and word-of-mouth, but their adoption is hampered due to financial, technological and legal constraints.

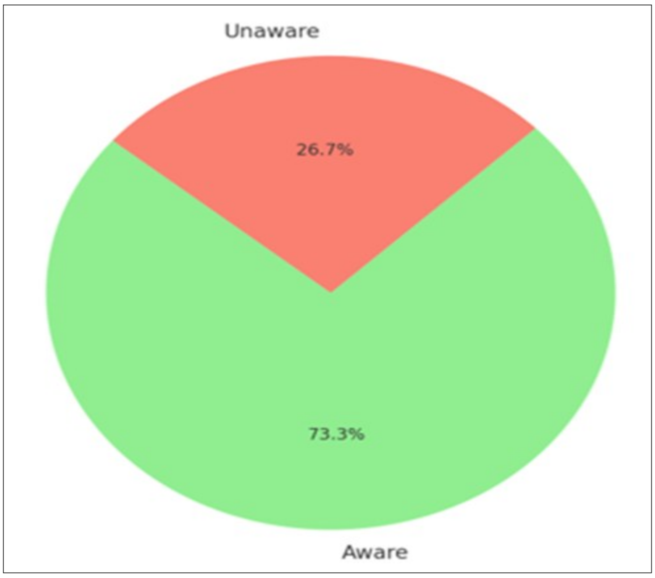

Fig. 1. Awareness of drone technology.

Association between demographic factors and awareness of drones

Table 2 explains the findings of a regression study that analyzed the relationship between awareness of drones and several demographic characteristics. Crop type has a coefficient of 0.446, which shows a significant positive correlation (p = 0.037) with an odds ratio (Exp(B)) of 1.562. This explains that people who work with crop types are more likely to be aware of agricultural drones than those who don't work with crop types. Education has an Exp(B) of 1.613 and a coefficient of 0.478, which suggests that greater education levels can relate to increased awareness of drones. However, the data does not support this theory (p = 0.169). A negative correlation between farm size and drone awareness is -0.303, but it is not statistically significant (p = 0.296). This suggests no significant relationship exists between higher farm sizes and drone awareness. With a coefficient of 1.086 (p = 0.005) and an Exp(B) of 2.961, income level shows a significant positive relationship, indicating a substantial correlation between higher income levels and increasing awareness of drones. The constant term, which represents the baseline log odds of awareness when all other factors are zero, is -3.110 and is significant at p = 0.013. Overall, the data explains the significance of crop type and income level as significant demographic variables affecting drone awareness (10).

Chi-square test

Chi-square analysis was used to determine the relationship between the usage of drones in agriculture and variables including gender, crop type, farm size and income level. Table 3 shows the adoption of drone technology in agriculture among 120 respondents. A majority (61.67%) have already adopted drone technology, while a minority (38.33%) have not yet adopted it. Further study reveals that the reason for non-adoption is due to Lack of awareness and accessibility. Some farmers are hesitant to replace traditional practices with new technologies due to concerns about familiarity. This suggests that drone technology is gaining traction in agriculture. However, there is still a significant number of potential adopters who may need more information or resources to make the switch.

Association between demographic factors and adoption of drones in agriculture

The association between various demographic factors and the adoption of drones in agriculture is indicated by Chi-square tests in Table 4. The results prove significant relationships across all factors examined. For gender, the Chi-square value is 6.656 with 1 degree of freedom (df) and a p-value of 0.0098, suggesting significant differences in drone adoption between male and female farmers. Education shows a Chi-square value of 10.010 (df = 4) with a p-value of 0.0402, indicating that educational level significantly influences the likelihood of adopting drone technology in agricultural practices (11). The analysis of farm size reveals a Chi-square value of 14.206 (df = 3) and a p-value of 0.0026, suggesting that farmers with different farm sizes show varying levels of drone adoption, with larger farms likely being more interested in adopting this technology (12). Crop type also indicates a significant relationship, with a Chi-square value of 8.747 (df = 3) and a p-value of 0.0328, indicating the kind of crops grown can influence a farmers' decision to adopt drones. Lastly, income level shows the strongest association, with a Chi-square value of 19.206 (df = 3) and a p-value of 0.0002, highlighting that higher income levels significantly correlate with increased adoption of drone technology in agriculture (11).

Impact of drone technology by propensity score matching

Propensity Score Matching (PSM) was used in this study to calculate the effect of agricultural drone adoption on farmers' income levels. After accounting for various confounding variables affecting adoption and income, PSM was used to compare the income levels of farmers who adopted agricultural drone technology (treated group) and those who did not (control group). The outcome model was based on matching techniques and the matching process was performed using a logit model to predict the propensity scores. The findings are presented below in Table 5.

The results of a treatment-effects estimation using propensity-score matching to analyze the impact of drone technology adoption on farmers' income levels, based on a sample of 120 observations, are given in Table 5. The table reports the Average Treatment Effect on the Treated (ATET), which quantifies the difference in income levels between farmers who adopted agricultural drone technology (treatment group) and those who did not (control group). The coefficient for adaptation is 1.145946, indicating that, on average, farmers who adopted drone technology experienced an increase in income levels by approximately 1.15 units compared to their non-adopting counterparts. This finding is statistically significant, with a z-value of 8.42 and a p-value of 0.000, demonstrating strong evidence that the adoption of drones positively influences income. The standard error is 0.1361756, suggesting a high level of precision in the estimate. The 95% confidence interval ranges

Table 2. Association between demographic factors and awareness of drones

	Coefficient (B)	S.E	Significance	Exp (B)
Crop type	.446	.214	.037	1.562
Education	.478	.347	.169	1.613
Farm size	-.303	.290	.296	.739
Income level	1.086	.382	.005	2.961
Constant	-3.110	1.254	.013	.045

Table 3. Adoption of drone technology in agriculture

S.No	Adoption (yes/no)	Number of respondent	Percent
1.	Yes	74	61.67
2.	No	46	38.33
Total		**120**	**100**

Table 4. Association between demographic factors and adoption of drones in agriculture

S.No	Particulars	Chi-square value	df	p-value
1	Gender	6.656	1	0.0098
2	Education	10.010	4	0.0402
3	Farm size	14.206	3	0.0026
4	Crop type	8.747	3	0.0328
5	Income level	19.206	3	0.0002

Table 5. Impact of drone technology adoption on farmers' income levels

Treatment-effects estimation **Number of observations = 120**
Estimator: propensity-score matching Matches: requested = 1
Outcome model: matching min = 1
Treatment model: logit max = 19

Income level	coefficient	Std. Err.	z	p>|z|	95% conf. Interval
ATET Adaptation (1 vs 0)	1.145946	.1361756	8.42	0.000	0.879 to 1.413

from 0.879 to 1.413, confirming that the true effect is likely between these values. These results provide compelling evidence that drone technology can significantly enhance farmers' income levels (11), highlighting its potential as a valuable tool in modern agricultural practices.

Factors influencing drone adoption

This study gave twelve statements to the sample respondents to identify the significant factors influencing drone technology adoption. The details of KMO and Bartletts' test are shown in Table 6. It could be inferred from Table 6 that the KMO measure of sampling adequacy is 0.704, more significant than 0.5. Bartletts' test of sphericity has a chi-square value of 633.701, which is essential at the 0.000 level. It could be concluded that factor analysis is suitable for further data analysis. The details of the total variables explained are given in Table 7.

The total variance explained by the extracted factors is presented in Table 7. Four components have eigenvalues more significant than one, explaining a cumulative variance of 77.166%. The first component explains 32.012% of the variance, the second explains 22.223 Percent, the third explains 11.524% and the fourth explains 11.407%. The details of the rotated component matrix are given in Table 8.

The factor loadings obtained after varimax rotation are presented in Table 8. Factor loadings having values equal to or greater than 0.5 are considered. The first component had five-factor loadings with values greater than 0.5, followed by the second component with three-factor loadings greater than 0.5, followed by the third and fourth components with two-factor loadings greater than 0.5. These components are assigned suitable names based on their factors and the details are given in Table 9.

Table 6. KMO and Bartletts' Test

KMO and Bartletts' Test		
Kaiser- Meyer- Olkin Measure of Sampling Adequacy.		.704
	Approx. Chi-Square	633.701
Bartletts' Test of Sphericity	df	66
	Sig.	.000

Table 8. Rotated component matrix

Rotated Component Matrix[a]				
	Component			
	1	2	3	4
Efficient spraying	.891			
Time effective	.869			
labour efficient	.843			
Water saving	.840			
Convenience	.828			
Yield		.946		
Credit access		.933		
Cost effectiveness		.819		
Farm size			.832	
Disease detection			.772	
Weather condition				.832
Legal implication				.734

The components and factors influencing the adoption of drone technology in agriculture, along with their associated variances, are presented in Table 9. The first component, efficiency, accounts for 32.012% of the total variance and highlights several advantages of agricultural drone usage, such as enhanced efficiency in spraying chemicals, reduced spraying time compared to traditional methods, increased labour efficiency, water conservation and overall convenience in a chemical application similar results were documented (13,14). The second component, Economic factors, represents 22.223% of the variance and highlights the economic benefits of drones,

Table 9. Components and factors components and factors

Components	Variance Percent	Factors
Efficiency	32.012	Increasing the efficiency of spraying chemicals Reduces spraying time compared to Increasing labour efficiency Water saving Convenient for spraying chemicals
Economic factors	22.223	Drones help to increase crop yield Credit access for agricultural drone Drones are cost-effective tools for
Farm-related factors	11.524	Farm size can influence the adoption of Helps to detect plant diseases
External factors	11.407	Weather conditions for spraying Legal regulation regulated drone use

Table 7. Total variables explained (principal component analysis)

Total Variance Explained						
Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	4.432	36.930	36.930	3.841	32.012	32.012
2	2.593	21.609	58.539	2.667	22.223	54.235
3	1.161	9.672	68.211	1.383	11.524	65.759
4	1.075	8.955	77.166	1.369	11.407	77.166
5	.749	6.243	83.409			
6	.647	5.388	88.797			
7	.547	4.561	93.358			
8	.300	2.496	95.854			
9	.255	2.123	97.977			
10	.151	1.255	99.232			
11	.051	.423	99.655			
12	.041	.345	100.000			

including their role in boosting crop yield, improving access to credit for agricultural drone purchases and being a cost-effective investment for farmers. Similar results were documented (11). The third component, Farm-related factors, accounts for 11.524% of the variance and suggests that factors like farm size can significantly influence the adoption of drone technology and the ability to detect plant diseases through aerial monitoring. Lastly, External factors contribute 11.407% of the variance, focusing on how weather conditions impact the timing of drone spraying operations and the influence of legal regulations governing drone usage in agriculture. Collectively, these components and factors provide a comprehensive view of the multifaceted reasons driving the adoption of drone technology in agricultural practices.

Barriers hindering the usage of drone technology in agriculture

The adoption of drone technology in agriculture faces several barriers, which impact farmers' willingness and ability to utilize this technology (8). The following figure presents the barriers hindering the usage of drone technology among the sample respondents, ranked by Henry Garrett Ranking. The ranking indicates that the Lack of availability of rental-based services is the most significant barrier, with a Henry Garrett ranking of 93.8. Lack of incentives (ranked 2nd) and Lack of service centres (ranked 3rd) are also prominent barriers (15,16), reflecting the need for better support systems and incentives to encourage adoption. High maintenance costs (17) and the requirement for specialized knowledge and skills rank 4th and 5th, respectively (18), highlighting the ongoing expenses and learning curve associated with drone technology. High initial cost ranks 6th. This suggests that the high initial costs of purchasing drones concern farmers (19). Regulatory and legal constraints, meteorological parameters, return on investment and internet connectivity are also important factors (19), though they rank lower in comparison (19-21). Addressing these barriers is essential for increasing the adoption of drone technology in agriculture. Providing financial support, improving access to service centres and offering training programs can help mitigate some of these challenges and promote the benefits of drones to farmers (Fig. 2.).

Conclusion

The research proves a considerable correlation between farmers' awareness and adoption of agricultural drone technology and demographic characteristics, farm size, crop type and education level. Most drone adopters had medium-sized farms that concentrated on vegetable crops and were middle-aged, male and well-educated. The results show that awareness and adoption of drones are positively related to larger farms and higher income levels and gender plays a significant influence, with male farmers being more influenced to use drone technology in their farming practices. Furthermore, farmers who are highly educated are more likely to support drone usage. Drones are primarily used in agriculture to spray pesticides for plant protection, but there is growing interest in using them for crop monitoring and health evaluation. The propensity score matching analysis findings highlight the potential financial advantages of incorporating drone technology into agricultural practices by indicating that its adoption raises farmers' income levels.

Policy implications suggest offering subsidies or low-interest loans to reduce the high initial cost of drones, particularly for small and medium farmers. Training programs, hands-on workshops and technical support are essential to enhancing farmers' skills and confidence. Establishing drone service centres, maintenance facilities and a clear regulatory framework will promote adoption. Incentives for early adopters could also encourage broader use. Future researchers should focus on longitudinal studies to assess long-term impacts, explore drone use across different regions and crop types and investigate the integration of drones with AI and IoT for better decision-making and precision farming. These measures will help unlock drones' full potential to improve productivity and farmers' income. The study emphasizes the importance of improved agricultural technologies like drones and their accessibility to increase farmers' income and productivity.

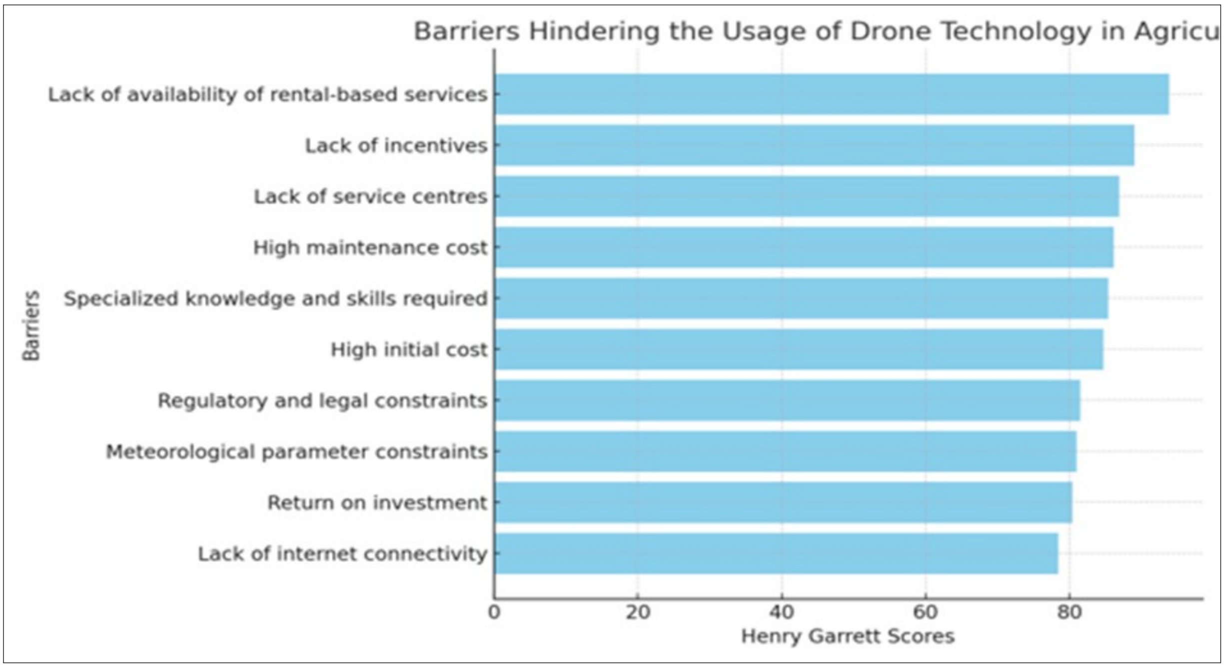

Fig. 2. Barriers hindering the usage of drone technology in agriculture.

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Authors' contributions

RB contributed to collecting the data, writing it and preparing the original draft. SS contributed to collecting material, guiding the preparation of the manuscript, reviewing, editing and supervising it. ND contributed by developing the ideas, reviewing the manuscript and helping procure research grants. PK helped edit, summarize and revise the manuscript. MP helped summarize and revise the manuscript.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interest to declare.

Ethical issues: None

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