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The Adoption of Drones Spraying Application in Bagan Terap, Malaysian Paddy Field: Farmer Perspectives and Technology Acceptance

Nurhamid Maulana, Akmal Hakim, Zahari, Mohd Khairy*, Mustaffha, Samihah, Ruslan, Nur Aziera, Shamsi, Siti Mariam & El Pebrian, Darius

Agricultural Technology Research Initiative Group, Faculty of Plantation and Agrotechnology, Universiti Teknologi MARA Cawangan Melaka, Kampus Jasin, 77300 Merlimau Melaka, MALAYSIA.

*Corresponding author: khairyzahari@uitm.edu.my

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Abstract: Drones are a recent innovation in Malaysia's agriculture sector. In rice fields, spraying pesticides manually can be hazardous for farmers. Drones offer a safer, more efficient alternative, potentially reducing spraying time by at least 33% compared to traditional methods. However, drone adoption by farmers remains limited. This study investigates farmers' risk perceptions and willingness to adopt drone technology in the IADA region. Using a survey of 88 farmers in IADA, Bagan Terap, and analyzed with SPSS, this paper found a positive outlook towards drone use. Correlation analysis revealed significant relationships between farmers' attitudes, social influence, economic factors, perceived risk, and their willingness to adopt drones. Applying the technology acceptance model, regression analysis showed that attitude was the strongest predictor of drone adoption intentions. These findings suggest that addressing farmers' attitudes, along with social and economic factors, could promote drone usage in agriculture.

Keywords: Drone, farmer perception, paddy cultivation, risk management

1. Introduction

In the present era, technology is progressively evolving in numerous domains. The agricultural sector has experienced significant advantages as a result of technical improvements. Unmanned aerial vehicles (UAV), also known as drones, are technologies used in agriculture. A UAV is an aircraft that operates without a human pilot on board. The user can control it remotely, or it can follow a pre-programmed flight path autonomously (Berner & Chojnacki, 2017). By utilizing UAVs, farmers can reduce their dependence on human labour and simultaneously decrease their expenses (Daponte et al., 2019). In the field of agriculture, farmers are required to employ smart farming techniques in order to acquire accurate documentation and agricultural data. UAVs are highly accurate electronic devices used in smart farming. A farmer can optimise decision-making by utilising a drone (Nordin et al., 2021). The employment of UAV has become a prevalent practice in agricultural management, mostly driven by the affordability of drones and the seamless integration of the Internet of Things (IoT) and cloud computing. Drone Map Planner (DMP) is a cloud-based robotics network that allows for real-time tracking, interaction, and control of robots and drones via the Internet. Drone Map seeks to optimize UAV operations by integrating UAVs with cloud technology. This integration allows for the virtualization of UAV connections and the offloading of resource-intensive computations from the UAVs to the cloud (Allouch et al., 2019). Drones in the agricultural sector oversee the development of trees and cattle, regulate the spread of illnesses, and manage the presence of weeds and chemicals. Drone technology is currently employed not only for crop monitoring but mostly for the transportation of payloads, such as pesticide and herbicide treatments (Giles & Billing, 2015). Consequently, this technology has the potential to mitigate labour shortages while simultaneously enhancing spraying effectiveness. Moreover, the use of drones for pest and disease control can help reduce the risk of pesticide and herbicide toxicity (Kedari et al., 2016). The use of drones for pest and disease control has the benefit of swift execution without causing any harm to the land or the crop (Berner & Chojnacki, 2017). In addition, drones have the capability to swiftly traverse field crops and effortlessly modify the spraying altitude relative to the plants (Faiçal et al., 2014).

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Corresponding author: khairyzahari@uitm.edu.my

While chemical spraying played a crucial role in paddy management, not all techniques proved to be efficient and beneficial. For a considerable duration, knapsack spraying served as one of the manual spraying techniques employed in Malaysia. A limited number of farmers in Malaysia have initiated the utilization of drones for the purpose of pesticide spraying. These findings indicate that a minority of farmers possess knowledge and embrace the utilization of drones for the purpose of managing paddy fields. Many rice farmers, predominantly in their forties, were not yet familiar with unmanned aerial vehicles (UAVs), which were already being utilized in many countries, including Malaysia. Farmers were ignorant of the potential of drones to optimize spray time, reduce labor expenses, and conserve energy, ultimately leading to long-term production gains and increased income. Due to insufficient knowledge regarding the advantages of utilizing drones, farmers have not yet embraced and acknowledged the usage of drones in paddy fields for crop security (Rosedi & Shamsi, 2022).

This study aims to investigate farmers acceptance of drone technology in paddy fields within the Bagan Terap region of Kuala Selangor. Objectives include the assessing farmers' attitudes towards drone applications, identifying key factors influencing farmers' willingness to adopt drone technology, examining the relationship between social influence, economic factors, and farmers' decisions regarding drone adoption.

2. Methodology

This research employs a cross-sectional study design to investigate farmers' acceptance of drone technology in paddy fields and assess the factors influencing their acceptance. The study is conducted in the IADA (Integrated Agricultural Development Area), specifically Bagan Terap, Malaysia. In Bagan Terap, the number of farmers with UAVs is estimated to be about 887. A sample of 88 farmers is selected using a stratified random sampling technique to ensure representation from various backgrounds. The conceptual framework that depicts in Figure 1 shows the relationship between several factors influencing farmer’s decisions to adopt drone technology for use in their paddy fields. The key elements include, drone Technology which is the central innovation being considered by farmers, risk perception which is farmers' evaluation of potential risks associated with drones (e.g., safety, privacy, regulations), social influence & economies which is the impact of social factors (peers, leaders, government) and economic factors (costs, efficiency, ROI) on farmers' decisions and lastly, technology acceptance model which is a framework analysing how perceived usefulness, ease of use, and social norms influence technology adoption.

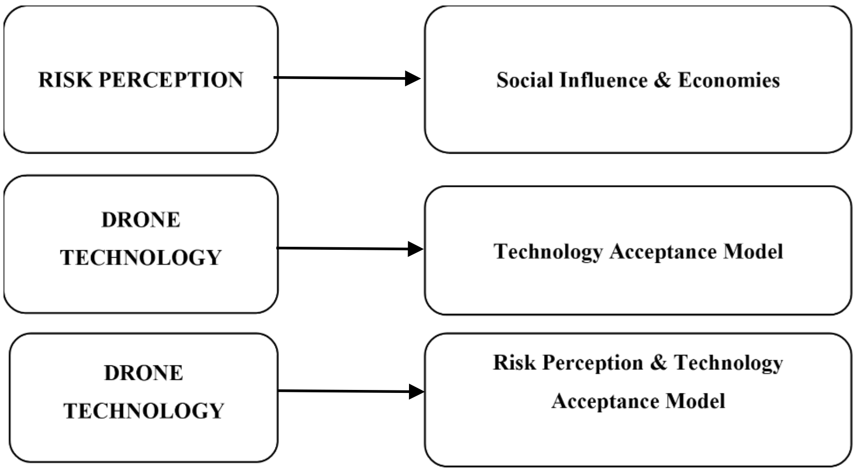

Fig. 1: Research procedure

The case study would employ simple random sampling to collect data. Simple sampling involves choosing a random subset of subjects from a population to serve as opinion experts. The location of this study is in Bagan Terap, Sabak Bernam district of Selangor, Malaysia as shown in Figure 2. It is known for its beautiful paddy fields, which are a popular tourist destination.

A subset of farmers from IADA in Bagan Terap, Selangor, are the participants in this case study. This is due to their increased susceptibility to encountering occupational hazards while operating unmanned aerial vehicles (UAVs). A selection of farmers will participate in this research investigation and provide responses to all the inquiries on the questionnaires. Referring to Table 1, the required sample size of farmers for the 4 blocks of paddy fields, while Figure 2 displays the aggregate area and the overall count of farmers from IADA cover about 1,479 ha.

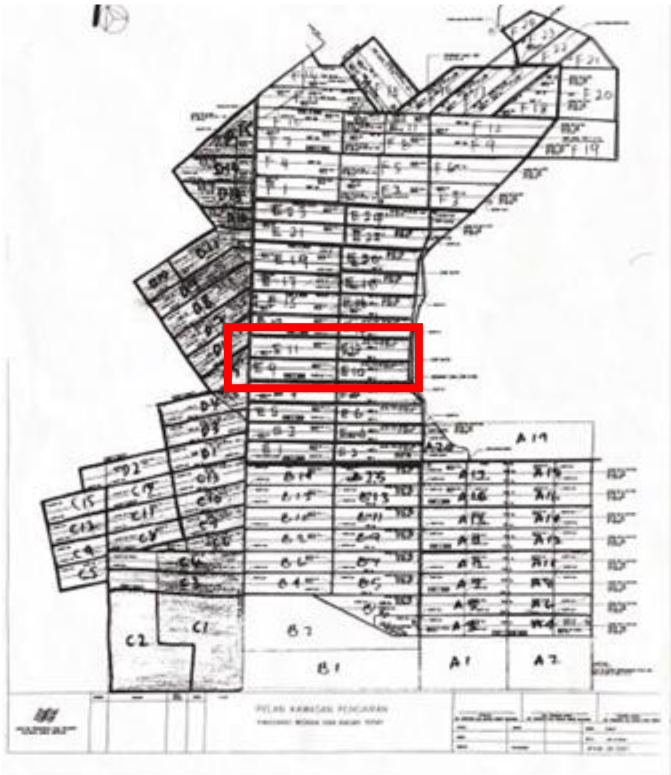

Fig. 2: Four blocks of paddy field plan area in Bagan Terap, Selangor, Malaysia

Table 1: Total number of farmers in Bagan Terap E9, E10, E11 and E12.

Area	Blocks	No. of Farmers
Bagan Terap	E9	30
	E10	23
	E11	31
	E12	25
	TOTAL	110

The Raosoft Sample Size Calculator is utilized for the purpose of determining the appropriate sample size for finite populations. This formula is widely accepted in research for calculating the minimum required sample size when dealing with a finite population, such as the number of farmers in the study area. The sample size consists of 88 out of the total 110 populations of farmers in paddy fields across the 4 blocks in Bagan Terap.

3. Data Collection

Structured questionnaires are used to obtain data from the chosen farmers. The survey has a combination of closed-ended questions and Likert-scale questions in order to collect quantitative data. A survey will be conducted to assess farmers' inclination to embrace drone technology for agricultural purposes in rice fields. Nevertheless, in order to cater to farmers or responders who may encounter difficulties in filling out the questionnaire in English or Bahasa Malaysia, this questionnaire will be made available in both languages. The questionnaires are divided into eight sections and have a total of 74 questions.

3.1 Data Analysis

Descriptive Analysis:

This journal provides a thorough analysis of farmers' perspectives on the use of drone technology in rice fields. To depict the participants responses, the process entails summarizing crucial information, including means and frequencies, to depict the responses of the participants. Descriptive analysis is a method of data analysis that helps to clarify, illuminate, or summarize data points in a usable way, allowing trends to develop that meet all of the data requirements.

Correlation Analysis:

To explore the relationships between various independent variables (e.g., social influence, economic factors) and dependent variables (e.g., farmer acceptance), a correlation analysis is performed. This analysis helps assess the strength and direction of associations between the variables, providing insights into potential connections.

Regression Analysis:

Using the technology acceptance model as a framework, regression analysis is employed to identify the most influential factors among the independent variables in predicting farmer acceptance of drone technology. The Beta values are examined to determine the relative impact of each independent variable on the dependent variable. Multiple linear regression will be used in this study. Other than that, multiple regression needs more than one independent variable to be able to make the accurate prediction about dependent variable which in the case of this study. The following is the formula:

$$Y = \alpha + B1X1 + B2X2 + B3X3 + B4X4 + \varepsilon$$

Y = Drone Technology (Dependent Variable)
A = Constant
B1 – B4 = Coefficient to be estimated
X1 = Independent Variable
X2 = Independent Variable
X3 = Independent Variable
X4 = (ε) = Error term

4. Results and Discussion

Table 2 presents demographic information collected from a survey of farmers in Bagan Terap, Sabak Bernam, Selangor. The data includes details on the gender, age, place of residence, marital status, education background, experience managing paddy fields, paddy field size, number of employees, ownership status of the land, type of enterprise run, and average monthly income of the farmers.

Table 2: Demographic table of the survey. Several notable trends emerged, painting a comprehensive picture of the surveyed population.

Demographic Information	Total	Percentage
Gender		
Male	79	89.8
Female	9	10.2
Age		
19–29-year-old	8	9
30-39	21	23.9
40-49	29	33
50-year-old and above	30	34
Are of Residence		
Urban	2	2
Semi-urban	23	26.1
Rural	63	71.6
Marital Status		
Single	12	13.2
Married	73	83
Divorced	2	2.3
Bachelor/widowed	1	1
Education Background		
Primary School	7	8
Secondary School	65	73.9
Diploma/Higher School Certificate	11	12.5
Bachelor Degree	5	5.7
Experience in managing paddy field		
1–5 years	11	12.5

continued

6–9 years	34	38.6
10–19 years	36	40.9
20 years and above	7	8
Paddy field size		
1–5 acres	60	68.2
6–10 acres	19	21.6
11–15 acres	7	8
16 acres and above	2	2.3
Number of employees		
1–10 persons	82	93.2
11–20 persons	5	5.7
21-30 persons	1	1.1
Ownership status		
Owner	69	78.4
Rent	17	19.3
Land lease	2	2.3
Type of enterprise run		
Family farm	36	40.9
Large enterprise	2	2.3
Small enterprise	47	53.4
No enterprise / work with people	3	3.4
*Average income monthly**		
RM 1,000 - RM 1,800	69	78.4
RM 1,900-RM 2,600	13	14.8
RM 2,700-RM 3,600	3	3.4
RM 3,700-RM 5,000	2	2.3
RM 5,000 and above	1	1.1

*RM = Malaysian Ringgit (1 RM = 0.2304 USD during the study)

Predominantly, the sample was male, constituting a significant 89.8% of the respondents. This male dominance in the demographic is reflective of the studied region's workforce composition. Age-wise, most of the participants were in the 50 years and above age bracket, indicating a matured demographic actively involved in the respective fields. This age group's prevalence suggests a workforce with potentially extensive experience and knowledge in their domains. When considering the area of residence, a vast majority (71.6%) of the respondents resided in rural areas. This trend is indicative of the rural-centric nature of the activities, possibly paddy field management. Marital status presented a clear trend towards married individuals, who made up 83% of the sample. This predominance could suggest a stable familial structure within the demographic, which might influence various socio-economic aspects of the community. The educational background of the majority was at the secondary school level (73.9%), highlighting the educational attainment level prevalent in the region. This could have implications for the types of skills and knowledge available within the workforce.

In terms of experience in managing paddy fields, the most common range was 10–19 years (40.9%), suggesting a highly experienced group in this sector. This length of experience can be crucial in understanding the depth of expertise and traditional knowledge present in the community. Regarding the size of the paddy fields, fields ranging from 1–5 acres were the most common, covering 68.2% of the sample. This size range could reflect the landholding patterns and agricultural practices predominant in the area. The workforce size in most enterprises was between 1–10 persons (93.2%), indicating a prevalence of small-scale operations. This could point towards a more localized, community-driven approach to enterprise management in the region.

Ownership status was predominantly 'owner' (78.4%), a trend that suggests a strong sense of ownership and personal investment in the enterprises or land under consideration. The type of enterprise most run was a small enterprise (53.4%), which aligns with the trends observed in workforce size and ownership status. This indicates a leaning towards small-scale, perhaps family-run, business models in the region.

Lastly, the most common income bracket was between RM 1000 - RM 1800 (78.4%), pointing towards a specific economic bracket dominating this demographic. This income range could have significant implications for understanding the economic conditions and spending power of the population.

4.1 Correlation Analysis of Demographic Data

The finding of the correlation analysis of the demographic data as depicted in Table 2, first is the education and income. The data suggests surprisingly little correlation between higher education levels and higher income within this demographic. Secondly, the experience and field size. The most experienced farmers (10-19 years) tended to manage smaller paddy fields (1-5 acres), indicating a potential lack of correlation between experience and field size. Third is the age and enterprise type. Older farmers (50+) were more likely to operate smaller enterprises. Fourth, is marital status and residence. Married farmers were predominantly found in rural areas. Lastly, gender and education. Most participants were male with a secondary school education.

4.2 Drone Technology for Spraying Application in Paddy Fields

The findings of this study primarily centred on a descriptive analysis, which highlighted a predominantly positive attitude among farmers regarding the use of drone technology in paddy fields. A significant portion as shown in Table 3 were the 88 farmers surveyed from IADA in Bagan Terap expressed supportive views on the adoption of drones for agricultural activities.

Table 3: Descriptive statistics of correlation analysis

Descriptive Statistics				
Questionnaire	**N**	**Mean**		**Std. Deviation**
	Statistic	**Statistic**	**Std. Error**	**Statistic**
Familiar With Drone	88	3.99	.066	.616
Used Drone at Paddy Field	88	4.11	.073	.685
Farmers Believe on Increase Job Performance in The Farm	88	4.10	.065	.607
Farmers believe on potential to alter farmers' daily work, routines, interactions, experiences, choices, and deliberation.	88	4.16	.056	.523
Ability In Increase Farm Productivity	88	3.65	.071	.662
Assumption Drone in Increase the Profit and Improve Farmers Livelihood	88	3.94	.075	.701
Valid N (list wise)	88			

*Note: 1=Strongly Disagree (SD), 2=Disagree (D), 3=Neutral (N), 4=Agree (A), 5=Strongly Agree (SA)

The table presents descriptive statistics for a survey conducted among 88 farmers, regarding their perceives of drone technology in agricultural settings, specifically in paddy fields. The responses are measured on a Likert scale from 1 (Strongly Disagree) to 5 (Strongly Agree). The survey of 88 farmers in the study revealed a notably positive reception towards drone technology within the agricultural sector. With an average score nearing 4, the farmers are quite familiar with drones, suggesting a considerable exposure to this technology. They also perceive the use of drones in paddy fields as favorable, indicated by a slightly higher average score of 4.11, which implies that they not only recognize but also appreciate the practical benefits of drones in agriculture.

Furthermore, the farmers strongly believe, as shown by an average score of 4.10, that drones can enhance job performance on farms. This is reinforced by an even higher average score of 4.16 for the belief that drones have the potential to transform their daily work, interactions, and decision-making processes. This reflects an acknowledgment of the significant impact that drone technology could have on the traditional farming routines. However, when it comes to the ability of drones to increase farm productivity, the farmers' agreement is somewhat less, with a mean score of 3.65. This score still reflects a general agreement but indicates a more cautious optimism about the efficiency gains from using drone technology. Finally, the farmers hold a moderately high expectation, with an average score of 3.94, that drone technology could improve their profitability and livelihood. This suggests that while there is optimism about the economic benefits of drones, there may also be some reservations that warrant further attention. The statistical results indicate a positive attitude among surveyed farmers towards the use of drones for spraying. Farmers primarily anticipate improvements in efficiency and economic outcomes from drone adoption.

5. Risk Perceive of Drone Awareness in Paddy Fields

The survey then continued with descriptive analysis of risk perceive for drone application in paddy field as shown in Table 4.

Table 4: Descriptive statistics of risk perceive of drone application.

Descriptive Statistics				
Questionnaire	N	Mean		Std. Deviation
	Statistic	Statistic	Std. Error	Statistic
The Safety on Drone Technologies	88	3.95	.070	.659
The Risky on Drone Technologies	88	2.83	.099	.925
The Safeness on Drone Compares Other Technologies	88	3.97	.061	.576
The Beneficial on Drone Technology to Workers and Farmers	88	4.16	.060	.565
The Threaten on Technology Drone to Workers and Farmers	88	2.82	.107	1.001
Ability to Reduce Chemical Wastage	88	3.97	.066	.615
Valid N (list wise)	88			

*Note: 1=Strongly Disagree (SD), 2=Disagree (D), 3=Neutral (N), 4=Agree (A), 5=Strongly Agree (SA)

The survey conducted with 88 participants revealed that farmers generally perceive drone technology as safe, as indicated by a mean score of 3.95. Despite recognizing some risks, which is reflected in the lower mean score of 2.83, farmers tend to disagree that drones are particularly hazardous. Comparatively, drones are seen as safer than other technologies, with a mean score of 3.97 suggesting a relative trust in their safety over alternative methods.

Farmers strongly agree that drone technology is beneficial to their work, demonstrated by the highest mean score of 4.16, highlighting a clear acknowledgment of the positive impact drones have on agricultural efficiency and productivity. Conversely, with a mean score of 2.82, there is a tendency among farmers to disagree with the notion that drones present a threat to their work and well-being.

Additionally, farmers concur with the idea that drones can reduce chemical wastage on farms, as shown by another high mean score of 3.97. This indicates an appreciation for the environmental and economic advantages of drone use in agriculture. While there is a consensus on the safety and benefits of drones, the standard deviation, especially for the perceived threat of drones (1.001), suggests that opinions on this aspect vary more than others. Overall, the survey illustrates a predominantly positive perceive of drone technology, with minor reservations about the associated risks.

6. Correlation Analysis

In the conducted analysis as shown in Table 5, the correlation between farmers' risk perceive of drone technology adoption and social influence was found to be moderately positive ($r = .528$, $p < .001$), suggesting that an increase in social influence is associated with an increase in perceived risk. Moreover, a stronger positive correlation was observed between risk perceive and economic factors ($r = .601$, $p < .001$), indicating that economic considerations might play a more substantial role in shaping the perceived risk associated with drone adoption. Additionally, the relationship between social influence and economic factors affecting farmers demonstrated a moderate positive correlation ($r = .540$, $p < .001$), implying that these two factors are interrelated. As either social influence or economic factors increase, the other tends to rise as well. These significant correlations, each with a p-value of less than .001, reinforce the conclusion that both social and economic variables are influential in determining farmers perceives of risk when considering the adoption of drone technology. This insight suggests that any strategies aimed at promoting drone technology in agricultural practices should not only address the technological aspects but also the socio-economic context influencing farmers' attitudes and decisions.

Table 5: Correlation analysis

		Risk Perceive on Adoption of Drone	Socially Influencing Farmers	Economies That Affect Farmers
Risk Perceive on Adoption of Drone	Pearson Correlation	1	.528**	.601**
	Sig. (2-tailed)		<.001	<.001
	N	88	88	88
Socially Influencing Farmers	Pearson Correlation	.528**	1	.540**
	Sig. (2-tailed)	<.001		<.001
	N	88	88	88
Economies That Affect Farmers	Pearson Correlation	.601**	.540**	1
	Sig. (2-tailed)	<.001	<.001	
	N	88	88	88

**. The correlation is significant at the 0.01 level.

The statistical analysis delineated in Table 6 investigates various constructs in relation to drone technology, which is the focal point of the study as a dependent variable. The study found an extraordinarily strong and statistically significant positive correlation ($r = 0.775$, $p < 0.001$) between attitudes towards drone technology and the technology itself. This robust correlation suggests that favorable attitudes towards drone technology are strongly associated with the technology's use, features, or functionality.

Furthermore, a significant and strong positive correlation was observed between the perceived usefulness of drone technology and the technology itself ($r = 0.691$, $p < 0.001$). This indicates that as the perceive of the technology's usefulness increases, so does its association with the technology's adoption or consideration for adoption. The relationship between drone technology and the perceived ease of use also demonstrates a strong positive correlation ($r = 0.594$, $p < 0.001$).

This finding implies that the ease with which individuals can use drone technology is significantly related to the technology's presence or use. Additionally, the perceived behavioral control over drone technology exhibits a strong positive correlation with the technology ($r = 0.665$, $p < 0.001$).

This result suggests a significant association between the control individuals feel they have over the technology and the technology itself. Moreover, the attributes of usability items related to drone technology show a strong positive correlation ($r = 0.530$, $p < 0.001$). This indicates a substantial relationship between the technology's usability aspects and the technology itself.

Lastly, the influence of social factors on drone technology adoption is also positively correlated ($r = 0.507$, $p < 0.001$). This correlation is strong and significant, which suggests that social influence is an important factor in the acceptance and use of drone technology.

Table 6: Correlation between Drone Technology towards Attitude, Perceived Usefulness, Perceived Ease of Use, Perceived of Behavior Control, Attribute of Usability Items and Social Influence.

Variable	Correlation Coefficient (r)	Significance (p-value)	Relationship Strength	Direction
Attitude	0.775	< 0.001	Very Strong	Positive
Perceived Usefulness	0.691	< 0.001	Strong	Positive
Perceived Ease of Use	0.594	< 0.001	Strong	Positive
Perceived Behavioral Control	0.665	< 0.001	Strong	Positive
Attributes of Usability Items	0.530	< 0.001	Strong	Positive
Social Influence	0.507	< 0.001	Strong	Positive

Note: All correlations are significant at the 0.01 level, indicating strong relationships with positive linear directions.

Table 7: Correlation between Risk Perceive on Adoption of Drone towards Attitude, Perceived Usefulness, Perceived Ease of Use, Perceived of Behavior Control, Attribute Of Usability Items, Social Influence and Drone Technology.

Variable	Correlation Coefficient (r)	Significance (p-value)	Relationship Strength	Direction
Attitude	0.569	< 0.001	Strong	Positive
Perceived Usefulness	0.553	< 0.001	Strong	Positive
Perceived Ease of Use	0.566	< 0.001	Strong	Positive
Perceived Behavioral Control	0.519	< 0.001	Strong	Positive
Attributes of Usability Items	0.422	< 0.001	Moderate	Positive
Social Influence	0.501	< 0.001	Strong	Positive
Drone Technology	0.520	< 0.001	Strong	Positive

Note: All correlations are significant at the 0.01 level, indicating strong relationships with positive linear directions.

In conclusion, the study provides valuable insights into the multifaceted nature of drone adoption in agriculture. By addressing perceived risks, improving the technology's usability and control, and fostering a positive social environment, stakeholders can effectively promote the adoption of drone technology among farmers. This could lead to significant benefits for the agricultural sector, such as increased efficiency, improved yields, and reduced costs.

7. Regression Analysis

In order to achieve the objective of to determine the most dominant factor, regression analysis was used to analyse the dependent and independent variables. Table 8 and 9 shows the regression analysis for risk perceive on adoption of drone. The data indicates that the correlation coefficient (R) between the independent variable and the dependent variable is 0.647. The coefficient of determination (R square) was 0.419, indicating that there is a 42% perceived risk associated with the introduction of drones. Which means, social influence and economic factors, together, account for 42% of the reasons why farmers perceive drone adoption as risky or not. The remaining 58% of the variation in perceived risk is due to other factors. These other factors could be anything from personal beliefs and past experiences to technological literacy and the specific characteristics of the drones themselves.

Table 8: Model summary of risk perceive on adoption of drone.

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.647[a]	.419	.405	1.93642

a. Predictors: (Constant), Economies That Affect Farmers, Socially Influencing Farmers

Table 9: Regression coefficient of risk perceived on adoption of drone.

Coefficients						
		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	3.337	2.356		1.416	.160
	Socially Influencing Farmers	.316	.108	.287	2.922	.004
	Economies That Affect Farmers	.423	.093	.446	4.538	<.001

a. Dependent Variable: Risk Perceive on Adoption of Drone

Therefore, the nominal from unstandardized coefficients (B) can be presented on multiple regression models is $Y=3.337 + 0.287X1 + 0.446X2 + \varepsilon$. Where, Epsilon ($\varepsilon$) represents the error term in the regression equation. It accounts for the unexplained variance in the dependent variable, which is the 58% discussed earlier. It encompasses all the factors not included in the model that also influence the perceived risk of drone adoption.

The regression coefficient in the preceding multiple linear regression analysis indicates the impact of independent factors on the dependent variable. The analysis found that variables pertaining to social influence on farmers and economic issues influencing farmers have a beneficial impact on their perception of risk regarding the use of drones, as seen by the favourable Beta value. Evaluating the p-value established the importance of the value, with values below 0.05 being deemed significant. The constant value is 3.337, signifying that when the components of social impact on farmers and the economic factors affecting farmers remain unchanged or have a value of zero, the perceived risk associated with employing drones will be 3.337. Farmers who are influenced by social factors have a regression coefficient of 0.287. The p-value for the impact of social influence on farmers is 0.004, which demonstrates statistical significance since it falls below the threshold of 0.05. The regression coefficient for economies affecting farmers is 0.446. The p-value for the influence of economies on farmers is 0.001, signifying statistical significance as it falls below the threshold of 0.05. Therefore, multiple linear regression analysis $Y=3.337 + 0.287X1 + 0.446X2 + \varepsilon$, Analysis showed that variables of socially influencing farmers and economies that affect farmers toward the risk perception on adoption of drone through the positive value of Beta. Hence, the significant value was measured by p-value which are smaller than 0.05 is significant.

The constant value is 3.337, it means that if socially influencing farmers and economies that affect farmers are constant or equal to zero (0), risk perception on adoption of drone will equal to 3.337. Socially influencing farmers has coefficient regression of 0.287. The p-value for socially influencing farmers is 0.004 and it is significant since the p-value is less than 0.05. Economies that affect farmers have coefficient regression of 0.446. The p-value for economies that affect farmers is 0.001 and it is significant since the p-value is less than 0.05.

Table 10 shows the model summary of variables attitude, perception usefulness, perception ease of use, perceptions of behaviour control, attribute of usability items and social influence toward drone technology. While, Table 11 shows the Coefficient of variables attitude, perception usefulness, perception ease of use, perceptions of behaviour control, attribute of usability items and social influence toward drone technology.

Table 10: Model summary of variables attitude, perception usefulness, perception ease of use, perceptions of behavior control, attribute of usability items and social influence toward drone technology.

Model Summary				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
1	.812[a]	.659	.634	1.57587

a. Predictors: (Constant), Social Influence, Perceive of Behavior Control, Attitude, Perceive Ease of Use, Attribute of Usability Items, Perceive Usefulness.

Table 11: Regression coefficient of variables attitude, perception usefulness, perception ease of use, perceptions of behavior control, attribute of usability items and social influence toward drone technology.

Coefficients[a]						
		Unstandardized Coefficients		**Standardized Coefficients**		
Model		**B**	**Std. Error**	**Beta**	**t**	**Sig.**
1	(Constant)	3.232	1.851		1.746	.085
	Attitude	1.055	.189	.670	5.579	<.001
	Perceived Usefulness	.066	.125	.071	.529	.598
	Perceived Ease of Use	.038	.102	.043	.369	.713
	Perceived Of Behavior Control	.225	.107	.278	2.107	.038
	Attribute Of Usability Items	.014	.196	.009	.070	.944
	Social Influence	-.218	.103	-.246	-2.106	.038

a. Dependent Variable: Drone Technology

Therefore, $Y = 3.232 + 0.67X1 + 0.071X2 + 0.043X3 + 0.278X4 + 0.009X5 + (-0.246) X6 + \varepsilon$.

Where Y is Multiple linear regression analysis result above shows the influence of independent variables to dependent variable based on the regression coefficient. Analysis showed that variables of attitude, perception usefulness, perception ease of use, perceptions of behavior control, attribute of usability items and social influence toward drone technology through the positive value of Beta except social influence which is negative. Hence, the significant value was measured by p-value which are smaller than 0.05 is significant. The constant value is 3.232, it means that if attitude, perception usefulness, perception ease of use, perceptions of behavior control, attribute of usability items and social influence are constant or equal to zero (0), drone technology will equal to 3.232.

Attitude has coefficient regression of 0.67. The p-value for attitude is 0.001and it is significant since the p-value is less than 0.05. Perception usefulness has coefficient regression of 0.071. The p-value for perception usefulness is 0.598 and it is not significant since the p-value is more than 0.05. Perception ease of use has coefficient regression of 0.043. The p-value for perception ease of use is 0.713 and it is not significant since the p-value is more than 0.05. Perceptions of behavior control has coefficient regression of 0.278. The p-value for perception usefulness is 0.038 and it is significant since the p-value is less than 0.05. Attribute of usability items has coefficient regression of 0.009. The p-value for attribute of usability items is 0.944 and it is not significant since the p-value is more than 0.05. Social influence has coefficient regression of -0.246. The p-value for perception usefulness is 0.038 and it is significant since the p-value is less than 0.05.

Table 12: Model summary

Model Summary				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
1	.814[a]	.663	.634	1.57568

a. Predictors: (Constant), Social Influence, Risk Perception on Adoption of Drone, Perception of Behavior Control, Attitude, Perception Ease Of Use, Attribute Of Usability Items, Perception Usefulness

Table 13: The influence of independent variables to dependent variable based on the regression coefficient.

Coefficients						
		Unstandardized Coefficients		**Standardized Coefficients**		
Model		**B**	**Std. Error**	**Beta**	**t**	**Sig.**
1	(Constant)	2.616	1.949		1.342	.183
	Risk Perceive on Adoption of Drone	.087	.086	.084	1.010	.316
	Attitude	1.018	.193	.646	5.277	<.001
	Perceived Usefulness	.064	.125	.069	.510	.612
	Perceived Ease of Use	.017	.104	.019	.162	.872
	Perceived Of Behavior Control	.216	.107	.268	2.021	.047
	Attribute Of Usability Items	.031	.197	.020	.160	.873
	Social Influence	-.225	.104	-.254	-2.168	.033

a. Dependent Variable: Drone Technology

Therefore, $Y = 2.616 + 0.084X1 + 0.646X2 + 0.069X3 + 0.019X4 + 0.268X5 + 0.02X6 + (-0.254) X7 + \varepsilon$.

The above result as shown in Table 12 and Table 13 are the multiple linear regression analysis. Which demonstrates the impact of independent factors on the dependent variable, as indicated by the regression coefficient. The analysis revealed that all variables, except for social influence, had a positive beta value. These variables include risk perception, attitude, perceived usefulness, perceived ease of use, perceived behavior control, attributes of usability items, and social influence towards drone technology. Therefore, the significance of the value was determined based on the p-value, where values smaller than 0.05 were considered significant. The constant value is 2.616.

This implies that if the factors of risk perception on adoption of drones—attitude, perceived usefulness, perceived ease of use, perceived behavior control, attribute of usability items, and social impact—are all set to zero (0), the value of drone technology will be 2.616. The coefficient of regression for risk perception in the adoption of drones is 0.84. However, the p-value for this relationship is 0.316, which is greater than the conventional significance threshold of 0.05. This indicates that we cannot conclude a statistically significant relationship between risk perception and drone adoption in this study. The coefficient of regression for attitude is 0.646. The p-value for attitude is 0.001, indicating statistical significance as it is below the threshold of 0.05. The coefficient of regression for the perception of usefulness is 0.069. The p-value for perceived usefulness is 0.069, which indicates that it is not statistically significant since it is above the threshold of 0.05. The coefficient of regression for the perceived ease of use is 0.019. The p-value for the perceived ease of use is 0.872, indicating that it is not statistically significant as the p-value exceeds 0.05. The regression coefficient for the perception of behavior control is 0.268. The p-value for perceived usefulness is 0.047, which indicates statistical significance as it is below the threshold of 0.05. The usability items have a regression coefficient of 0.02. The p-value for the attribute of usability items is 0.944, indicating that there is no significant effect. This is because the p-value exceeds the threshold of 0.873. The coefficient of regression for social influence is -0.254. The p-value for perceived usefulness is 0.033, indicating statistical significance since it is below the threshold of 0.05.

The findings highlight the complex interplay of factors influencing drone adoption in agriculture. While economic considerations and a positive attitude towards technology are the most influential factors, social influence plays a dual role, affecting both risk perception and adoption in different ways. These insights can be used to inform strategies aimed at promoting drone adoption among farmers. For instance, focusing on the economic benefits of drones and addressing concerns related to their cost-effectiveness may be more effective than solely emphasizing their technological features or ease of use. Additionally, understanding the social dynamics at play within farming communities can help tailor outreach and educational efforts to maximize the positive impact of social influence while mitigating any potential negative effects.

4.0 Conclusion

In conclusion, the analysis consistently demonstrates that attitudes, perceived usefulness, perceived ease of use, perceived behavioural control, usability attributes, and social influence are all significantly and positively correlated with the acceptance of drone technology for spraying applications. Each of these factors is crucial and provides insights into the multifaceted acceptance and integration of drone technology in the context studied.

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Conflict of Interest

The authors declare no conflicts of interest.

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