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Drone Technology: Unlocking the Potential of Agricultural Input through Services Market in Pondicherry District

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ABSTRACT

The paper explores the transformative impact of drone technology in agriculture, particularly in paddy farming. Drones, also known as Unmanned Aerial Vehicles (UAVs), offer significant advantages in precision farming by enabling efficient application of fertilizers, pesticides, and other chemicals. This study compares the cost, returns, and resource use efficiency between paddy farmers using drones and those not using them. A multi-stage stratified random sampling method was employed in Pondicherry district, covering 60 respondents. Analytical tools such as resource use efficiency analysis, decomposition analysis, and Partial Least Square-Structural Equation Modelling (PLS-SEM) were used to evaluate the data. The findings suggest that farmers using drones experienced a 6.04 per cent reduction in per-acre cultivation costs and higher net income than non-users. The decomposition analysis revealed that technical changes contributed to 51.66 per cent of the variation in output, while changes in input use contributed 40.95 per cent. The PLS-SEM analysis indicated a positive relationship between drone usage and improved cost-time management, highlighting the potential of drones to enhance productivity and sustainability in agriculture by reducing labor costs and minimizing environmental impact

Keywords: Paddy, input level, cost and returns, resource use efficiency, drone utilization, cost and time management.

JEL codes: O33, Q1, Q12, Q16, Q18

I

INTRODUCTION

Precision farming is beneficial for accurately locating geographical positions using remote sensing. It lays a strong foundation for various modern farm activities, such as spraying fertilizers and pesticides, seed sowing, irrigation, harvesting, and crop monitoring. This shift from traditional to mechanized agriculture paves the way for intensive farming. Precision farming maximizes resource use at minimal cost and time, contributing to sustainable agriculture (Parameswari and Walia, 2019). Unmanned Aerial Vehicles (UAVs), popularly known as drones, are aircraft operated remotely by a human operator using an onboard computer. The term 'Drone' stands for Dynamic Remotely Operated Navigation Equipment. Recently, drone technology has gained popularity in agriculture, assisting in farm management studies, cost and time minimization, improved yields, and effective spraying techniques (CIMMYT, 1993). Drones uniquely benefit farmers, enhancing efficiency, improving yields, and reducing cultivation costs. The drone market is expected to rise to 32.40 billion US dollars, indicating that the agricultural sector will greatly benefit from drones compared to conventional methods (Pinguet, 2021). The international market for drone sprayers in the agriculture and allied sectors is expected to grow by 36 per cent, reaching a value of 5.70 billion US dollars by 2025 (TropoGo, 2022). However, this technology is still

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in its early adoption stage, with many farmers hesitant to embrace it due to fears of crop failure, lack of knowledge, and insufficient training.

This study explores the potential of drone technology in the given study area, mainly focusing on costs, returns, resource use efficiency in paddy farms, the decomposition of output changes due to drone technology, and the relationship between drone utilization and cost-time management.

II

METHODOLOGY

2.1 Sampling Procedure

A multi-stage stratified random sampling technique was selected with Pondicherry district as the universe, blocks in the study area as the first stage unit, commune panchayats as the second stage sampling unit, villages in the selected commune panchayats as the third stage unit and the paddy farmers form the fourth unit of sampling. Five paddy farmers using drones and five non-users were chosen randomly from each selected village. Hence, the ultimate sample consisted of 30 drone users and 30 non-users, and the total sample was 60 respondents.

2.2 Collection of Data

The primary data were collected from the sample respondents of the two categories, *viz*., drone user and non-user, by personal interview method with the help of a comprehensive and pre-tested schedule during March-April 2024. The interview schedule for farmers consisted of specific and detailed information on the quantity of inputs used and the cost and returns obtained in cultivating paddy by drone users and non-users.

III.

TOOLS OF ANALYSIS

3.1 Analytical Approach in the Estimation of Costs and Returns

Cost concepts such as cost A_1, A_2, B_1, B_2, C_1, C_2, and C_3 were used to calculate the profitability of production in farm households.

3.2 Resource Use Efficiency

The Cobb-Douglas production function specified for paddy farms in the present study area is given below:

$$Y = aX_1^{\beta 1} X_2^{\beta 2} X_3^{\beta 3} X_4^{\beta 4} X_5^{\beta 5} X^{ut}$$

Where,

YD = Yield of paddy/ acre

X_1 = Human labour (number of labours/ acre)

X_2 = Machine labour (number of hours/ acre)

X_3 = Irrigation (number of irrigations/ acre)

X_4 = Manures and fertilizers (kg/ acre)
X_5 = Crop protection chemicals (litres/ acre)
u_t = Error term
A = Intercept/ constant
$b_1 \ldots\ldots\ldots b_6$ = Regression coefficients

The Cobb-Douglas form of production function was transformed into a logarithmic linear form, and parameters (coefficients) were analyzed using the Ordinary Least Square method as given below.

$$\ln YD = \ln a + \beta_1 \ln X_1 + \beta_2 \ln X_2 + \beta_3 \ln X_3 + \beta_4 \ln X_4 + \beta_5 \ln X_5 + u_t \ln e$$

3.3 Decomposition Analysis

The factors influencing drone technology and their contribution have been estimated by decomposing the overall variation in paddy farmers' income due to usage of drone equipment into the proportion due to technical change and the proportion due to the input change. The decomposition model proposed by Bisaliah (1977) was used in this study.

Besides decomposing the total change, the value of inputs saved with drone technology and the value of surplus output obtained were also estimated. The empirical model is derived as follows.

$$\text{Log } G_1 = \log Z_1 + a_1 \log HL_1 + b_1 \log ML_1 + c_1 \log I_1 + d_1 \log F_1 + e_1 \log P_1 + u_1 \quad \ldots.(1)$$

$$\text{Log } G_2 = \log Z_2 + a_2 \log HL_2 + b_2 \log ML_2 + c_2 \log I_2 + d_2 \log F_2 + e_2 \log P_2 + u_2 \quad \ldots.(2)$$

Equations (1) and (2) are the Cobb-Douglas functions in log form for drone user and non-user categories in paddy cultivation, respectively.

Where,

G = Gross Income (Rs.)
HL = Expenditure on Human labour (Rs.)
ML = Expenditure on machine labour (Rs.)
I = Expenditure on irrigation (Rs.)
F = Expenditure on manures and fertilizers (Rs.)
P = Expenditure on crop protection chemicals (Rs.)

Z_1 is the scale parameter, and a_1, b_1, c_1, $d_{1,}$ and e_1 denote output elasticities of the respective inputs, u_1 is a random disturbance term, independently distributed with zero mean and finite variance.

Taking differences between equations (2) and (1), adding similar terms, subtracting the similar parameters, and rearranging them, the equation could be written as:

$$\text{Log}\,\frac{G_2}{G_1} = \log \frac{Z_2}{Z_1} + [(a_2 - a_1) \log HL_1 + (b_2 - b_1) \log ML_1 + (c_2 - c_1) \log I_1 + (d_2 - d_1) \log F_1 + (e_2 - e_1) \log P_1] + [a_2 \log \frac{H_2}{H_1} + b_2 \log \frac{ML_2}{ML_1} + c_2 \log \frac{I_2}{I_1} + d_2 \log \frac{F_2}{F_1} + e_2 \log \frac{P_2}{P_1} + (u_2 - u_1) \quad ...(3)$$

The attribution of technical change to overall variation in income is derived from equation (3). In contrast, the first and second bracketed terms measure percentage changes in income due to shifts in scale and slope parameters, respectively. The third bracketed term denotes the assessment of change in income due to variations in the inputs used per acre, given the percentage change in output by these inputs under drone technology. These three terms will together account for the total change in income.

3.3.1 Value of Inputs Saved Approach

With this approach, the resources required by non-users to produce per-acre levels of income in drone technology were estimated. The difference between this figure and the resources used to produce the income level using drone technology represents the inputs saved because of higher efficiency due to drone technology. The following expression was formulated to evaluate the inputs saved in terms of value due to drone usage:

$$R_{OT} = (1 + \frac{r}{100})\, R_{NT}$$
$$S_R = (\frac{r}{100})\, R_{NT}$$

3.3.2 Value of Surplus Output Obtained Approach

The value of surplus output obtained using drone equipment, the non-usage of drone technology, and the volume of inputs were estimated using the following formula.

$$\Delta Y = Y_{NT} - Y_{OT}$$

$(\Delta Y)(r)$ = value of surplus output due to technical change alone

Where,

Y_{NT} = Per acre output with use of drone technology

Y_{OT} = Per acre output without drone technology

R_{NT} = Human labour value, machine labour value, irrigation charges, manures & fertilizers, and crop protection technology used in producing Y_{NT}

R_{OT} = Value of selected inputs required to produce Y_{NT} without the use of drone technology

r = Percentage increase in output per acre under drone usage with the non-usage volume of all selected exogenous variables per acre

S_R = Value per acre of selected explanatory variables saved to produce Y_{NT} with drone usage.

3.4 Partial Least Square – Structural Equation Model

The PLS-SEM technique, a two-step modelling approach for data analysis introduced by Anderson and Gerbing (1988), was employed in this study. PLS-SEM consists of two distinct ways: the measurement approach and the structural approach.

The measurement approach served as a preliminary analytical tool. It assesses the reliability and validity of the data, which are crucial steps before proceeding to empirical analysis. It is widely acknowledged that unreliable or invalid data would render any subsequent empirical analysis futile due to potential issues with computed results. Once the Measurement approach was validated, the Structural approach was utilized to test hypotheses regarding the relationships between modelled variables. The Structural approach employed the bootstrapping technique to examine these relationships. Path analysis, an integral component of the Structural approach, constructed and evaluated the significance of these paths. Specifically, the PLS-SEM method was employed for evaluating Structural Equation Modelling (SEM) using an appropriate statistical software, SmartPLS 4.

IV

RESULTS AND DISCUSSION

The primary data collected from the sample respondents were analysed with the specific objectives outlined for the study. The results are presented below.

4.1 Cost and Returns

The cultivation cost was calculated for paddy crop separately for drone user and non-user categories by working out the share of each cost item in the total cost for cultivation and given in Table 1.

It is evident from Table 1 that the overall cultivation cost of paddy in the non-user category was Rs. 56,985.67 per acre, which is 6.04 per cent higher than the cultivation cost of the drone user category. Among the different cost components in paddy cultivation for the drone users, machine labour occupied the major share of 18.44 per cent, followed by human labour (9.60 per cent), fertilizer (9.58 per cent), manure (6.38 per cent), crop protection chemicals (3.38 per cent), seed (1.88 per cent), and irrigation (1.53 per cent). Whereas, in the non-user category of farms, the machine labour constituted 15.72 per cent, which is followed by fertilizer (13.64 per cent), human labour (10.49 per cent), manure (8.55 per cent), crop protection chemicals (6.03 per cent), seed (1.98 per cent) and irrigation (1.59 per cent).

Thus, it could be understood that the cost of human labour, seed, manures and fertilizers, crop protection chemicals, and irrigation were lower in the drone user category than in the non-user category. However, the machine labour cost was higher in the drone user category. Findings showed that the gross income from paddy by the drone user farms was higher, i.e., Rs. 76,698, compared to the non-user farms (Rs. 72,617). Consequently, the net income received by the drone user was much higher, accounting for Rs. 22,960, than the non-user category (Rs. 15,931). The net return per

TABLE 1. COST AND RETURNS OF SAMPLE PADDY FARMS

S. No (1)	Items (2)	Drone User (3)	Non-User (4)
1	Human labour	5,160.34 (9.60)	5,978.00 (10.49)
2	Machine labour	9,912.00 (18.44)	8,956.66 (15.72)
3	Seeds	1,013.80 (1.88)	1,133.33 (1.98)
4	Crop protection chemicals	1,820.00 (3.38)	3,466.67 (6.03)
5	Manures	3,433.33 (6.38)	4,873.33 (8.55)
6	Fertilizers	5,146.83 (9.58)	7,775.33 (13.64)
7	Irrigation charges	825.00 (1.53)	910.00 (1.59)
8	Depreciation (machinery and farm building)	400.00 (0.74)	400.00 (0.70)
9	Land revenue, cess, and taxes	140.33 (0.26)	157.33 (0.28)
10	Miscellaneous expenses (electricity, fuel, etc)	470.00 (0.87)	141.33 (0.25)
11	Interest on working capital @ 7 per cent	1,996.51 (3.71)	2,296.84 (4.03)
	Cost A_1	30,318.14 (56.42)	36,008.82 (63.33)
12	Rent paid for leased in land	6,183.33 (11.51)	5,013.33 (8.79)
	Cost A_2	36,501.48 (67.92)	41,122.15 (72.13)
13	Rental value of owned capital assets (excluding land)	1,448.25 (2.69)	693.00 (1.22)
	Cost B_1	37,949.73 (70.62)	41795.15 (73.34)
14	Rental value of owned land	10,423.33 (19.39)	9,520.00 (16.70)
	Cost B_2	48,372.72 (90.01)	51,315.15 (90.04)
15	Imputed value of family labour	480.00 (0.89)	490.00 (0.86)
	Cost C_1	38,429.73 (71.51)	42,285.15 (74.20)
	Cost C_2	48,852.72 (90.91)	51,805.15 (90.91)
	Cost C_3(Cost C_2 + 10 % of cost C_2)	53,737.99 (100)	56985.67 (100)
	Gross income	76,698.33	72,916.67
	Net income	22,960.34	15,931.01
	Returns per rupee	1.43	1.28

rupee was higher in the drone user category (1.43) than in the non-user category (1.28). Thus, the respondents using drone technology had realised significantly higher yield and returns from paddy. The decrease in fertilizer and pesticide usage in quantity and cost might be due to the uniform spraying of fertilizer using drones. Nevertheless, the lack of human labour supply was also an inevitable constraint in paddy cultivation. So, this new technology could be recommended for sustainable growth in agriculture.

4.2 Resource Use Efficiency in Paddy Cultivation

The Cobb-Douglas production function was fitted with yield as the outcome variable and inputs like human labour, machine labour, irrigation, manures & fertilizers, and crop protection chemicals as the predictor variables. The analysis was done separately for both categories. The results are presented in Table 2.

TABLE 2. ESTIMATES OF THE COBB-DOUGLAS PRODUCTION FUNCTION

S. No (1)	Variables (2)	Drone Users		Non-Users	
		Coefficients (3)	Standard Error (4)	Coefficients (5)	Standard Error (6)
1	Constant/Intercept	1.881	1.610	4.822***	0.378
2	Human Labour (Man days/acre)	0.405***	0.105	0.692***	0.119
3	Machine Labour (hours/acre)	0.287***	0.075	0.288***	0.058
4	Irriagtion (no/acre)	0.086	0.126	0.319**	0.076
5	Manures and Fertilizers (kg/acre)	0.429***	0.149	0.039	0.029
6	Crop protection chemicals (Litres/acre)	0.226*	0.012	-0.199	0.079
	R^2	0.72		0.77	
	Returns to Scale	1.43		1.14	

A perusal of the estimated production function revealed that the value of R square in the regressions was 0.72 in the drone user category and 0.77 in the non-user category, which implied that 72 per cent and 77 per cent of the variation in paddy yield was explained by the included predictor variables used in the model, respectively. The human labour, machine labour, manures, and fertilizers were positive and statistically significant on the drone user farms. Moreover, the use of crop protection chemicals was positive and significant. The regression coefficients of these input variables reveal that for every one per cent increase in these variables, *ceteris paribus* would result in 0.41, 0.29, 0.43, and 0.23 per cent increase in the paddy yield, respectively.

For the non-adopters, the coefficient of human labour, machine labour, and irrigation was positive and statistically significant at a one per cent level. The regression coefficients of these variables indicate that everyone per cent increase in the variables would result in 0.69, 0.29, and 0.32 per cent increase in the paddy yield, respectively. It means the scope for expanding the use of these inputs to increase the paddy yield.

The sum of production elasticities in the drone user category was 1.43, whereas in non-users, it was 1.14. This indicates that the increased return to scale prevailed in the sample farms in paddy production. More specifically, the returns to scale were higher in the drone user category than in the non-user category. In summary, incorporating drone technology in paddy cultivation has showcased improved resource use efficiency compared to non-users. Drones can enable precise input optimization and efficient operational management. Farmers can minimize resource wastage by leveraging these advancements, improving productivity, and promoting sustainable agricultural practices. Drone technology has the potential to revolutionize agriculture, making it more resource-efficient and environmentally friendly.

4.3 Decomposition Analysis

In decomposition analysis, using the values of production parameters and the input levels, the total change in per acre paddy output with the adoption of innovative practices, namely, drone usage, has been decomposed, and the findings are given in Table 3.

TABLE 3. ESTIMATES OF DECOMPOSITION ANALYSIS

S. No	Source of change	Percentage Attribution
1.	Technical change	51.66
2.	Change in inputs	40.95
a)	Human Labour	4.46
b)	Machine Labour	14.94
c)	Irrigation	0.17
d)	Manures and Fertilizer	13.46
e)	Crop protection chemicals	7.92
3.	Changes due to other factors	7.39
	Total due to all sources	100.00

It could be inferred from Table 3 that the attribution of technical change to the overall variation in output was found to be 51.66 per cent, since technical change influences the sources of output growth by altering the scale and slope parameters. It is understood that with the same level of per-acre inputs, 51.66 per cent more output could be obtained in the production process. The input changes under drone user farms contributed 40.95 per cent of the increased output. The contribution of machine labour was the highest, with 14.94 per cent, followed by manures and fertilizer (13.46), crop protection chemicals (7.92 per cent), human labour (4.46 per cent), and irrigation, with only a negligible share.

4.3.1 Value of Input Saved Due to Drone Usage

With the value of the inputs saved approach, the resources required to produce the drone usage level of output per acre by non-user were estimated, and the results are presented in Table 4.

TABLE 4. VALUE OF INPUT SAVED DUE TO DRONE USAGE

S. No (1)	Variable (2)	Value (3)
1	R_{NT}	26,297.50
2	R_{OT}	39,972.20
3	r (%)	0.52
	Value of input saved per acre in paddy cultivation (S_R)	13,674.70

It could be inferred from Table 4 that in the absence of drone technology, a farmer would have required an additional amount of Rs. 13,674.70 per acre to produce the drone-user income level. This magnitude of resource-saving was due to an upward shift in the production function or a downward shift in the unit cost function with drone technology. The outcomes support the findings obtained by Bisaliah (1977).

4.3.2 Value of Surplus Output obtained under Drone Usage

The additional quantity of output obtained with drone usage was estimated and given in Table 5.

TABLE 5. ESTIMATES OF SURPLUS OUTPUT OBTAINED UNDER DRONE USAGE

S. No (1)	Variable (2)	Value (3)
1	Y_{NT}	23.68 Quintals
2	Y_{OT}	22.30 Quintals
3	ΔY	1.38 Quintals
4	r (%)	0.52
	ΔY (r)	0.72 Quintals

The surplus output obtained in paddy cultivation using drones, without additional resource costs, was 1.38 quintals per acre (Table 5). Further, the per acre income of the drone user category was higher than the non-user category. The percentage increase in income per acre in the drone user category with the non-user category volume of all selected exogenous variables per acre was 0.52.

4.4 Time and Cost Management in Drone Usage

The PLS-SEM technique was used to evidence the observed relation between drone utilization and cost-time management.

4.4.1 Measurement Approach

The measurement approach in this study is used to evaluate the data validity and reliability, as depicted in Figure 1. The empirical results of the Measurement approach are mentioned in the following sections.

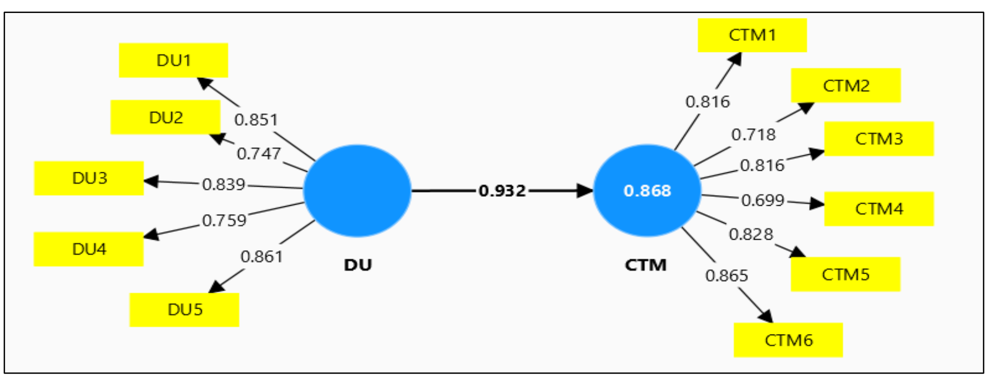


Figure 1. Illustration of Measurement Approach

4.4.1.1 Convergent Validity

Typically, convergent validity is assessed using factor loading values. A commonly accepted guideline suggests that factor loading values should exceed 0.4 to meet the criteria for convergent validity. The estimated values of convergent validity are given in Table 6.

TABLE 6. ESTIMATES OF CONVERGENT VALIDITY

S. No (1)	Items (2)	CTM (3)	DU (4)
1	CTM1	0.816	
2	CTM2	0.718	
3	CTM3	0.816	
4	CTM4	0.699	
5	CTM5	0.828	
6	CTM6	0.865	
7	DU1		0.851
8	DU2		0.747
9	DU3		0.839
10	DU4		0.759
11	DU5		0.861

Note: DU – Drone Utilization, CTM – Cost and Time Management

It is seen from Table 6 that the loading values of the mentioned items range between 0.699 and 0.865, confirming the existence of convergent validity in the data.

4.4.1.2 Discriminant Validity

Testing for discriminant validity is essential for achieving accurate results. According to Forner-Larcker's criteria, the diagonal values should exceed those in the other positions. The findings of discriminant validity are depicted in Table 7.

TABLE 7. FORNER-LARKER CRITERIA FOR DISCRIMINANT VALIDITY

S. No (1)	Constructs (2)	Cost and Time Management (CTM) (3)	Drone Utilization (DU) (4)
1	Cost and Time Management (CTM)	0.932	
2	Drone Utilization (DU)	0.793	0.813

It can be seen from Table 7 that this criterion was fulfilled. Hence, it denotes the existence of discriminant validity between drone usage and the cost-time management relationship in the data.

4.4.1.3 Construct Reliability and Validity

Cronbach's Alpha (CBa) assessed the data's internal consistency and reliability. As per the criterion, CBa values should surpass 0.5 to meet the requirement for data reliability. Moreover, the closer the values are to one, the higher the reliability of the data. Table 8 presents the results of CBa, demonstrating that the values for both constructs exceeded 0.5, indicating robust data reliability. Construct reliability (CR) has been used to double-check the reliability measures. The results of CR also showed that the variables were highly reliable for the analysis. The Average Variance Extracted (AVE) coefficient was employed to assess the convergent validity of each variable.

AVE values greater than 0.50 indicate the existence of convergent validity between the variables in the data.

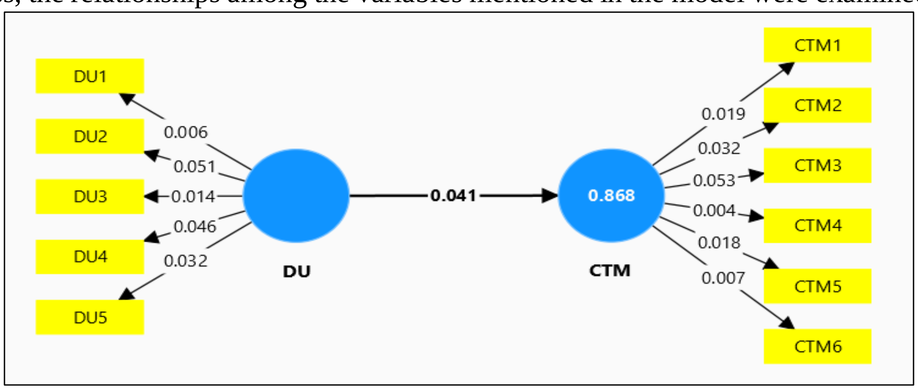
TABLE 8. ESTIMATES OF CONSTRUCT RELIABILITY AND VALIDITY

S. No	Item	Crohn-Bach Alpha (CBa)	Construct Reliability (CR)	Average Variance Extracted (AVE)
(1)	(2)	(3)	(4)	(5)
1	CTM	0.880	0.910	0.628
2	DU	0.871	0.907	0.661

Note: DU – Drone Utilization, CTM – Cost and Time Management.

4.4.2 Structural Approach

The structural approach is depicted in Figure 2. Using the bootstrapping process, the relationships among the variables mentioned in the model were examined.



Note: DU – Drone Utilization, CTM – Cost and Time Management

Figure 2. Illustration of Structural Approach

4.4.2.1 Collinearity Issue

The initial step in the structural model involved diagnosing collinearity issues. The Variance Inflation Factor (VIF) assessed collinearity among each construct variable. The results of VIF are presented in Table 9.

TABLE 9. ESTIMATES OF COLLINEARITY DIAGNOSTIC

S. No	Items	VIF
(1)	(2)	(3)
1	CTM1	2.710
2	CTM2	2.639
3	CTM3	3.234
4	CTM4	1.730
5	CTM5	2.704
6	CTM6	3.732
7	DU1	2.923
8	DU2	2.027
9	DU3	2.553
10	DU4	1.940
11	DU5	2.488

Note: DU – Drone Utilization, CTM – Cost and Time Management

It inferred that the problem of collinearity among each variable was not present in the data since the value of VIF did not exceed 5 in the CTM and DU variables.

4.4.2.2 Path Analysis

The last step of the structural approach was path analysis, which was conducted to derive the study's empirical findings. The coefficients of path analysis were used to examine the proposed hypotheses of the study. The coefficients of structural path analysis presented a p-value of less than 0.05. The results verified the presence of an actual relation between drone utilization and cost-time management, thus accepting the proposed hypothesis. Drone usage positively and significantly influenced cost and time management (β = 0.932, T =2.071, p < 0.041**). The results of path analysis are presented in Table 10.

TABLE 10. ESTIMATES OF PATH ANALYSIS

Path (1)	Coefficient (2)	Std Dev (3)	T stat (4)	p values (5)
DU -> CTM	0.932	0.450	2.071	0.041**
R-square	0.868			
R-square adjusted	0.864			

** Significant at 5 per cent level.

From Table 10, it could be inferred that the coefficient of CTM (0.932) was statistically significant at five per cent. The positive sign of the coefficient indicates a positive relation exists between DU and CTM. These results suggest that a one-unit increase in drone utilization is associated with a 0.932-unit increase in cost-time management. Furthermore, the R-square value (0.868) indicates that 86.80 per cent of the variation in cost and time management can be explained by drone usage.

To sum up, employing the PLS-SEM technique, this study examined the efficacy of drone usage on cost-time management in agriculture. Through meticulous evaluation of the measurement and structural approach, the proposed theoretical framework was substantiated with robust evidence of construct reliability, convergent validity, and discriminating validity. The path analysis further affirmed the significance of hypothesized relationships, providing empirical support for the positive effects of drone utilization on cost-time management. These, in turn, exerted substantial positive influences on drone utilization and cost-time management. These comprehensive analyses validate the proposed theoretical model, contributing valuable insights into enhancing drone usage in the study area.

V

CONCLUSION

In conclusion, drones have brought about a paradigm shift in agriculture, empowering farmers with precise and timely data collection, analysis, and intervention. The adoption of drone technology in agriculture has the potential to increase productivity, reduce costs and time, and ultimately contribute to minimize environmental impact. As drone technology advances, its impact on agriculture will continue to evolve, presenting new opportunities for innovation and improvement in the farming industry. Effectively harnessing the impact of drone technology in agriculture requires careful consideration of policy implications. Such policies would maximize the potential benefits of drone technology and ensure the sustainable and socially responsible implementation of this transformative tool.

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