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The Future of Farming: Unveiling Farmers' Intentions to Adopt UAVs in Agriculture

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ABSTRACT
Agriculture is critical to the sustenance of the world population and the economy of nations, yet it is plagued by intensifying challenges caused by climate change, resource scarcity, and escalating demand for food. Precision agriculture and, in the context of precision agriculture, Unmanned Aerial Vehicles (UAVs) have immense transformative capacity for increased efficiency and sustainability. This research considers the influence of Technology Awareness towards farmers' Perceived Value of UAVs and how it will affect their Intention to Use drone technology for agriculture. Adopting a structured questionnaire, information was gathered from 210 Navsari city farmers in the state of Gujarat, using the mixed non-probability sampling technique. Relationships between the crucial constructs were evaluated through Structural Equation Modeling (SEM) through Smart PLS. The results show that Technology Awareness has a strong effect on Perceived Value, and Perceived Value has a strong effect on Intention to Use. Technology Awareness does not directly affect adoption but plays a mediating role through Perceived Value. These findings are consistent with the Technology Acceptance Model (TAM) and Perceived Value Theory, stressing that while awareness is essential, perceived economic and functional values are important in making adoption choices. This research offers useful recommendations to policymakers, agricultural extension services, and technology companies that awareness campaigns need to demonstrate tangible benefits and cost-effectiveness. Financial incentives, training initiatives, and subsidies can also add perceived value and support UAV uptake.

Keywords: *Precision Agriculture, Unmanned Aerial Vehicles (UAVs), Technology Awareness, Perceived Value, Technology Adoption.*
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1. INTRODUCTION:

Agriculture is a sector that not only sustain world populations but also substantially contributes to economies of nations. Nevertheless, escalating pressure for food production, driven by environmental demands and scarce resources, is causing tremendous pressure on agriculture sector. Based on the recent statistics of Food and Agriculture Organization (FAO) and the United Nations, about 10.7% of the world's population is affected by acute severe food insecurity, and about 113 million people are facing extreme hunger (FAO report, 2024). Climate change, dwindling water resources, and the environmental impacts of intensive crop and livestock production further exacerbate these issues (Gomiero et al., 2011; Hrustek, 2020). Furthermore, changes in land use pose a risk to biodiversity, and farming emits greenhouse gases which are grave sustainability issues (Li et al., 2020)

To tackle the challenges, Sustainable Development goals (SDGs) of the United Nations, particularly SDG goal 2, aims to culminate hunger, achieve food security, enhance nutrition.

and promote sustainable agriculture (United Nations, 2015). Advanced technologies such as artificial intelligence (AI), the Internet of Things (IoT), unmanned aerial vehicles (UAVs), robotics, have the potential to transform agriculture by increasing its productivity, efficiency, and sustainability. Precision agriculture is proven to be a game-changing answer by using these cutting-edge technology to make data-driven decisions about pest control, fertilisation, irrigation, and planting (Puppala et al., 2023). Among these innovations, UAVs, commonly referred to as drones, have gained prominence due to their ability to operate under diverse weather conditions, offer cost-effective solutions, and provide high-resolution spatial and temporal data (Floreano & Wood, 2015; Pritt, 2014; Schirrmann et al., 2016).

Several developing countries, mainly in Asia, are under excessive population pressure as well as relatively low productivity levels in agriculture, in contrast with technologically evolved nations. India, with around 73% of its total population being associated with agriculture both directly and indirectly, also comes under such challenge because of dominant traditional methods, low rates of technology use, power shortages, and unskilled labour (Panjaitan et al., 2022). Conventional methods of pesticide application tend to lead to overuse of chemicals and pollution of the environment, calling for the implementation of automated technologies such as pesticide spraying robots (Meshram et al., 2022). To overcome these issues, the Government of India has prioritized the implementation of advanced precision technologies, including drone-based pesticide spraying, which provides even application, minimizes the use of chemicals, and reduces human exposure (PIB, 2022). The Government of Gujarat, as part of national initiatives, has initiated programs such as nano-urea spraying by drone to ensure precision farming and maximize the use of fertilizers (CMO Gujarat, 2024). It is intended to increase efficiency, lower environmental costs, and streamline farming technology, placing Gujarat at the forefront of agriculture drone technology.

Although a plethora of research has analyzed the use of drone technology in farming, most only concentrate on its technical aspects, for example, its efficacy in pesticide spraying and monitoring the health of crops. Few have explored the social-psychological elements that influence farmers' adoption behaviour. More importantly, current research fails to provide a thorough analysis of how Technology Awareness affects the Perceived Value of drones for farmers, further impacting their Intention to Use the technology. Previous research has largely examined economic and demographic considerations (Skevas & Kalaitzandonakes, 2020; Wachenheim et al., 2021) without regard for how the knowledge of applications by farmers in turn influences farmers' adoption processes. In addition, research has mainly focused on advanced agricultural economies, neglecting local contexts where smallholder farmers experience specific challenges, including financial limitations, technological literacy, and trust in innovation.

Additionally, although Perceived Value is generally recognized as a significant driver of technology acceptance (Zeithaml, 1988; Sweeney & Soutar, 2001), its mediating function between Technology Awareness and Intention to Use is not well examined in the agricultural UAV adoption context. This literature gap calls for a more in-depth theoretical model combining the Technology Acceptance Model (Davis, 1989) and Perceived Value Theory (Zeithaml, 1988) to explain the adoption decision-making process of farmers towards UAVs. Using Smart PLS for Structural Equation Modeling (SEM), this research attempts to fill this gap by empirically testing these relationships and making contributions that can guide strategies towards increasing drone adoption in agriculture.

2. LITERATURE REVIEW

In order to improve agricultural output and farmer's financial security, it is imperative that new agricultural technologies be adopted (Chavas & Nauges, 2020). Likewise, advancements in agricultural technologies have greatly impacted production techniques and agricultural productivity (Pathak et al., 2019). According to research, farmers don't always accept new methods or technology instantaneously (Diederen et al., 2003). Adoption, on the other hand, usually occurs when advances offer obvious advantages. (Pierpaoli et al. 2013) also underlined that the adoption process is still complicated and influenced by a number of factors, even with significant efforts to encourage farmers to accept new technologies.

Numerous factors influencing farmers' adoption of Unmanned Aerial Vehicles (UAVs) have been examined in the substantial research on UAV use in agriculture. (Zheng et al. 2019) found that most surveyed farmers are comfortable with UAV technology. Their study found that farmers' propensity to use UAVs was influenced by a number of factors, including perceived utility, convenience of use, familiarity with new technology, gender (male), and agricultural income ratio. According to (Skevas and Kalaitzandonakes, 2020), the adoption of UAVs is also significantly influenced by farmer perceptions of the economic and environmental benefits. Socioeconomic characteristics, such as farmer commitment to long-term farming, succession ambitions, and cooperation with neighbouring farmers, were also found to be important in adoption. More affluent farmers with increased access to risk capital were also noted to be more inclined towards adopting UAV technology.

(Michels et al. 2021) utilized the Technology Acceptance Model (TAM) to describe UAV adoption by German farmers and found that TAM explained 69% of variance in farmers' intentions to adopt drones. The research concluded that enhancing farmers' knowledge of farm-specific uses and enhancing their perceived ease of use of drones can increase adoption levels. In a Chinese study, Wachenheim et al. (2021) found a number of factors that had a positive impact on the adoption of UAVs for pesticide spraying, such as gender (male), proportion of income from agriculture, land area under cultivation, within-family village leadership, availability of borrowing channels, and favourable attitudes toward UAV technology.

In Türkiye, Parmaksiz and Cinar (2023) proved that government subsidies have a strong positive effect on farmers' UAV buying decisions. Instead of buying, though, farmers preferred to rent agricultural UAVs, frequently depending on cooperatives for rental purposes. The research also revealed that young farmers, especially those with high interest in technology and higher agricultural revenues, were more likely to adopt UAVs. Zainudin et al. (2023) also claimed that farmers' adoption of UAV technology is more related to its perceived usefulness and ease of use than its newness. If adopted widely, UAVs would have a profound effect on agricultural production. Suvittawat (2024) recently surveyed 410 Thai farmers and discovered that certain UAV characteristics—precision, durability, and ease of use—matched farmers' expectations, thus enhancing perceived value and making wider adoption more likely.

Overall, the literature summarize that a combination of demographic, technological, and economic factors are driving the use of UAVs in agriculture. Perceived utility, ease of use, financial capability, government incentives, and familiarity with UAV applications are the most influencing factors. UAVs are also likely to be incorporated into agricultural methods by younger farmers who have a sustained interest in the field and financial resources. Thus, by incorporating the two useful theoretical frameworks the Perceived Value Theory (Zeithaml, 1988) and the Technology Acceptance Model (TAM) (Davis, 1989), this study investigate the relationship between Technology awareness, Perceived

Value and Adoption Intention. According to TAM, perceived utility and perceived ease of use both of which depend on farmers' knowledge and understanding of how drones can improve agricultural efficiency determine technology adoption (Davis, 1989; Venkatesh & Bala, 2008). When farmers are properly informed regarding drone technology, they tend to understand its utility for precision farming and facile integration with existing agricultural operations. Perceived Value Theory also illustrates that adoption choices are influenced by an individual's assessment of the advantages of the technology in comparison to its expenses (Zeithaml, 1988; Sweeney & Soutar, 2001). Research indicates that greater awareness translates to higher perceived value, which in turn increases adoption intention (Kim, Kim, & Shin, 2019). In the agricultural industry, it has been proven that exposure to technology innovation and training initiatives positively affect perceived value and adoption willingness (Li et al., 2021).

On the basis of literature review and research gap identification, this research suggests the following conceptual framework that combines the Technology Acceptance Model (TAM) (Davis, 1989) and Perceived Value Theory (Zeithaml, 1988) to investigate UAV adoption for pesticides spraying by farmers.

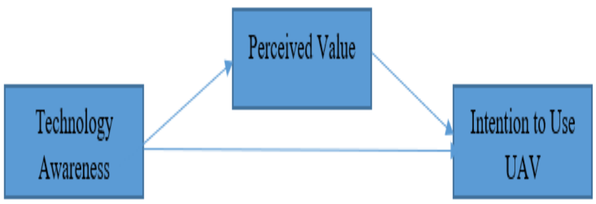


Figure1: Conceptual Framework

Hypotheses Development

H1: Technology Awareness positively influences Perceived Value of UAVs for pesticide spraying.

H2: Perceived Value positively affects farmers' Intention to Use UAVs for pesticide spraying.

H3: Perceived Value mediates the relationship between Technology Awareness and Intention to Use UAVs for pesticide spraying.

3. MATERIALS AND METHODS

The research was carried out in Navsari city, which is situated in the Navsari district of Gujarat, falling under the heavy rainfall belt of South Gujarat. The district has an area of 2,196 square kilometres and about 136,000 hectares of cropped area. The main economic activity in the area is agriculture, with major crops being paddy, sugarcane, and horticulture. Approximately 47% of the population of the district relies on allied activities and agriculture for their livelihood (Navsari citation). With the district's dominance in agriculture, knowledge of drivers for the adoption of drone technology by farmers is essential for encouraging precision farming and technological progress in the industry.

The research utilized a mixed non-probability sampling strategy by using convenience sampling and purposive sampling. At first, convenience sampling was employed to choose farmers on the basis of their willingness and availability to be part of the study. Later, purposive sampling was employed to choose farmers who were potential adopters of Unmanned Aerial Vehicles (UAVs) for agricultural purposes to ensure the sample was consistent with the research goals (Etikan, Musa, & Alkassim, 2016). 210 farmers from Navsari city were chosen using this combined sampling technique. Although the sampling procedure was not random, it made the sample accessible and relevant to the research.

A structured questionnaire was used to gather data from farmers. The questionnaire contained validated scales for measuring Technology Awareness, Perceived Value, and Intention to Use UAV technology in agriculture. The items of the scales were taken from existing research to make them reliable and valid in measuring the study constructs.

To test the proposed research model, Structural Equation Modeling (SEM) using Smart PLS was employed. Specifically, mediation analysis was conducted to examine the indirect effect of Technology Awareness on Intention to Use, mediated by Perceived Value. Smart PLS was chosen due to its effectiveness in handling small to medium sample sizes and its ability to assess both direct and indirect relationships between latent variables.

4. RESULTS

Table1: Demographic Breakdown

Items	Details	Frequency	Percentage
Gender	Male	187	89.05%
	Female	23	10.95%
Age	21 to 30 years	29	13.81%
	31 to 40 years	62	29.52%
	41 to 50 years	82	39.05%
	More than 50 years	37	17.62%
Education	No Formal Education	22	10.48%
	Primary School	38	18.10%
	Secondary School	49	23.33%
	Diploma/Certificate Course	42	20.00%
	Bachelor's or higher Degree	59	28.10%
Annual Agricultu	Less than 5 Lac	46	21.90%

ral Income			
	5 Lac to 10 Lac	98	46.67%
	11 Lac to 15 Lac	32	15.24%
	More than 15 Lac	34	16.19%
Farm Size	Less than 5 Acre	85	40.48%
	5 -15 Acre	67	31.90%
	15-25 Acre	39	18.57%
	More than 25 Acre	19	9.05%
Types of Ownership	Owned	153	72.86%
	Leased	28	13.33%
	Mortgage	22	10.48%
	Community based	7	3.33%
Types of Crops Grown	Sugarcane	65	30.95%
	Tobacco	32	15.24%
	Rice	21	10.00%
	Fruits	58	27.62%
	Vegetables	34	16.19%

The data provides valuable insights into the potential intention of farmers to use drones for pesticide spraying in agriculture. Given that 89.05% of the farmers are male and a majority (68.57%) are in the 31-50 years age group, there is a likelihood that these farmers may be more open to adopting technology-driven solutions like drone-based pesticide spraying, especially considering their experience in farming and exposure to modern agricultural practices. However, only 13.81% of farmers are below 30 years, a group typically more tech-savvy, which might slow down widespread adoption.

Educational background plays a significant role in technology adoption. The data shows that 28.10% of farmers have a Bachelor's degree or higher, and 23.33% have completed secondary education, indicating that a substantial portion of farmers possess the educational capacity to understand and implement drone technology. However, the presence of 10.48% farmers with no formal education could pose challenges in training and adoption.

Income level is another critical factor. With 46.67% of farmers earning between ₹5-10 lakh annually, they may have the financial ability to invest in drone technology, especially if cost-sharing models or subsidies are introduced. However, 21.90% of farmers earn below ₹5 lakh, indicating that affordability concerns could be a barrier for small-scale farmers.

Farm size also plays a crucial role in determining the feasibility of drone adoption. The data reveals that 40.48% of farmers own less than 5 acres, which may reduce the cost-benefit appeal of drone usage for them, as traditional spraying methods may be more cost-effective for small plots. However, farmers with larger farms (5-25 acres, 50.47%) might see greater efficiency and labour-saving benefits in drone technology.

Regarding land ownership, 72.86% of farmers own their land, meaning they have greater decision-making freedom in adopting drone technology. In contrast, leased and mortgage-based farmers (23.81%) may have limited control over technological investments, which could slow down adoption in certain cases.

Crop type also influences drone adoption. Sugarcane (30.95%) and fruit (27.62%) farmers may benefit more from drones due to precision spraying needs and high-value crop protection. However, tobacco (15.24%) and vegetable (16.19%) farmers may also find drones useful if the benefits outweigh the costs.

Table2: Measurement Model

	Constructs	**Factor Loading**	**VIF**	**Cronbach's alpha**	**Composite reliability**	**Average variance extracted (AVE)**
Intention to Use	IU1	0.698	1.640	0.886	0.893	0.691
	IU2	0.882	3.209			
	IU3	0.890	3.859			
	IU4	0.836	3.076			
	IU5	0.833	2.406			
Perceived Value	PV1	0.876	2.646	0.875	0.879	0.727
	PV2	0.839	2.020			
	PV3	0.827	2.191			

	PV4	0.867	2.845			
Technology Awareness	TA1	0.799	2.049	0.835	0.890	0.605
	TA2	0.836	1.887			
	TA3	0.724	1.701			
	TA4	0.903	2.843			
	TA5	0.590	1.535			

The assessment of construct reliability and validity confirms that the latent variables in this study—Technology Awareness (TA), Perceived Value (PV), and Intention to Use (IU)—demonstrate strong internal consistency and measurement quality. Cronbach's alpha (α) and Composite Reliability (CR/rho_a) were evaluated to measure internal consistency, with acceptable thresholds set at 0.7 or higher (Nunnally & Bernstein, 1994; Hair et al., 2019). The results indicate that PV and TA exhibit high reliability, with Cronbach's alpha values of 0.876 and 0.799, respectively, and composite reliability values well above 0.8, confirming internal consistency. IU has a Cronbach's alpha of 0.698, slightly below the 0.7 threshold, though its CR (0.886) indicates strong overall reliability. One item in TA (TA5) appears to contribute less to reliability, suggesting a potential area for refinement.

The Variance Inflation Factor (VIF) values are used to assess multicollinearity in the inner model, with values exceeding 5 or 10 indicating problematic multicollinearity (Hair et al., 2019). In this study, all VIF values are well below the threshold, ranging from 1.535 to 3.859, suggesting that there is no significant multicollinearity among the indicators for Intention to Use (IU), Perceived Value (PV), and Technology Awareness (TA). This indicates that the constructs are not excessively correlated, supporting the stability and reliability of the structural model.

Convergent validity was assessed using Average Variance Extracted (AVE), where a value ≥ 0.5 indicates that the construct explains a sufficient proportion of variance among its indicators (Fornell & Larcker, 1981). The AVE values for IU (0.691), PV (0.727), and TA (0.605) all surpass this threshold, confirming that the measurement items effectively capture their respective constructs. This strong convergent validity indicates that each construct is well represented by its observed variables.

Table3: Heterotrait-Monotrait (HTMT) Matrix

	IU	**PV**	**TA**
IU			
PV	0.827		
TA	0.538	0.741	

HTMT analysis verifies that the constructs of the study—Technology Awareness (TA), Perceived Value (PV), and Intention to Use (IU) drones for agricultural spraying—have sufficient discriminant validity. All HTMT values are below the suggested 0.90 threshold, so each construct is unique. The HTMT value between PV and IU (0.827) reflects a moderate relationship without over-lapping, whereas TA and PV (0.741) and TA and IU (0.538) also establish their conceptual distinction. These findings support the measurement model so that the constructs are not plagued by redundancy or collinearity, thus enhancing the reliability and validity of the structural model (Henseler et al., 2015; Hair et al., 2019).

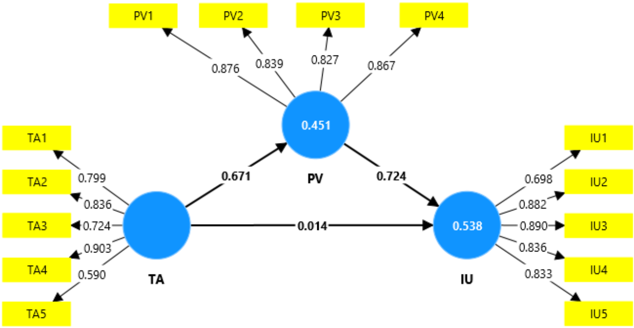
Table4: Fornell Larcker Criterion

	IU	**PV**	**TA**
IU	0.831		
PV	0.733	0.852	
TA	0.500	0.671	0.778

The Fornell-Larcker criterion outputs validate that the constructs in the research—Technology Awareness (TA), Perceived Value (PV), and Intention to Use (IU) drones for agricultural spraying—possess sufficient discriminant validity. The square roots of the AVE values for each construct (IU = 0.831, PV = 0.852, TA = 0.778) are higher than the correlations between the constructs (IU-PV = 0.733, IU-TA = 0.500, PV-TA = 0.671), which means that the constructs are sufficiently different. This reinforces the assumption that every construct reflects a distinctive dimension and is not highly correlated with the other constructs, ensuring discriminant validity of the model (Fornell & Larcker, 1981; Hair et al., 2019).

Table5: Structural Model

	Path Coefficient	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (O/STDEV)**	**P values**
PV -> IU	0.724	0.728	0.081	8.897	0.000
TA -> IU	0.014	0.005	0.085	0.164	0.870
TA -> PV	0.671	0.675	0.052	13.023	0.000



The structural model analysis by Smart PLS results in the direct relationships of Technology Awareness (TA) with Perceived Value (PV) and Intention to Use (IU), and the direct relationship of Perceived Value with Intention to Use. The path coefficients (β), standard errors, t-statistics, and p-values are used to identify the strength and significance of these relationships.

First, the Perceived Value (PV) and Intention to Use (IU) are found to be statistically significant and strong (β = 0.724, t = 8.897, p = 0.000). This indicates that farmers' perceived value of the benefit obtained from utilizing drones for spraying pesticides and fertilizers has a significant positive effect on their intention to use this technology. The large t-statistic (t > 1.96) and the p-value less than 0.05 validate that this relationship is statistically significant (Hair et al., 2021).

Second, the statistical significance between Technology Awareness (TA) and Intention to Use (IU) does not exist (β = 0.014, t = 0.164, p = 0.870). The small t-statistic (less than 1.96) and large p-value (greater than 0.05) suggest that technology awareness does not directly affect farmers' intent to utilize drones. This indicates that awareness of drone technology alone may not be sufficient to encourage farmers to adopt it, perhaps because of other variables like cost, perceived value, or user-friendliness (Venkatesh et al., 2003).

But the association between Technology Awareness (TA) and Perceived Value (PV) is both strong and statistically significant (β = 0.671, t = 13.023, p = 0.000). This implies that farmers with greater awareness of drone technology also view it as more valuable, which in turn can affect their intention to adopt it. The strong t-statistic and strongly significant p-value further support the strength of this association.

Table6: Mediation Analysis

	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (O/STDEV)**	**P values**
TA -> IU	0.486	0.494	0.083	5.841	0.000

The total indirect effect represents the influence of Technology Awareness (TA) on Intention to Use (IU) that occurs through the mediator, Perceived Value (PV). Since the direct effect of TA on IU (β = 0.014, p = 0.870) was found to be statistically insignificant, this result suggests that the relationship between TA and IU is fully mediated by PV. This means that technology awareness alone does not directly lead to farmers' adoption of drones; instead, it increases their perceived value of the technology, which in turn enhances their intention to use it.

A **t-statistic of 5.841** (greater than the critical value of 1.96) and a **p-value of 0.000** (less than 0.05) confirm that this mediation effect is statistically significant (Hair et al., 2021). The substantial indirect effect (β = 0.486) indicates that a higher level of technology awareness leads to a stronger perception of the value of drones, ultimately increasing the likelihood of adoption.

5. DISCUSSION

The demographic analysis reveals that mid-aged male farmers (31–50 years, 68.57%) are more involved in agricultural decision-making, particularly in adopting drone technology. A relatively educated respondent base (28.10% with a bachelor's degree or higher, 23.33% with secondary education) suggests potential for technology adoption, though 10.48% with no formal education may require additional training. Financial capacity also influences adoption, as 46.67% earn ₹5–10 lakh annually, indicating potential investment capability, while small-scale farmers (40.48%) may perceive drone adoption as cost-prohibitive. In contrast, larger farm owners (5–25 acres, 50.47%) may benefit more from efficiency gains. Land ownership is another key factor, with 72.86% owning their farms, enabling autonomous investment decisions. However, leased (13.33%) and mortgage-based (10.48%) farmers may face financial constraints, limiting their ability to invest in expensive agricultural technology.

The findings of this study provide empirical support for the Technology Acceptance Model (TAM) (Davis, 1989) and the Perceived Value Theory (Zeithaml, 1988) in the context of drone adoption for agricultural spraying. The results indicate that perceived value (PV) plays a crucial role in influencing farmers' intention to use (IU) drones, aligning with previous research that highlights the importance of perceived usefulness and value in technology adoption (Venkatesh & Davis, 2000; Venkatesh et al., 2003). The strong and significant relationship between PV and IU (β = 0.724, p = 0.000) confirms that farmers who perceive drones as beneficial and cost-effective are more likely to adopt them, consistent with studies in precision agriculture (Jiang et al., 2021; Klerkx & Rose, 2020).

Interestingly, technology awareness (TA) did not have a direct significant effect on IU (β = 0.014, p = 0.870), suggesting that awareness alone does not drive adoption, an insight that aligns with Rogers' (2003) Diffusion of Innovations theory. This finding reinforces the argument that knowledge of a technology must be complemented by perceived benefits to encourage adoption (Thong et al., 2006). However, TA had a significant impact on PV (β = 0.671, p = 0.000), demonstrating that greater awareness enhances perceived value, which, in turn, positively influences IU. This aligns with findings from prior research indicating that awareness fosters perceived benefits and cost-effectiveness, which are critical determinants of technology adoption (Park et al., 2019; Rana et al., 2022).

The analysis of indirect effects additionally supports that PV completely mediates the association between TA and IU, as evidenced by a significant total indirect effect (β = 0.486, p = 0.000). This indicates that awareness is required but only manifests through heightened value perception, reinforcing research claiming the mediating role of perceived value and usefulness in TAM models (Benbasat & Barki, 2007; Teo, 2011).

6. CONCLUSION

The work extends the Technology Acceptance Model (TAM) by embedding Perceived Value Theory to explicate drone acceptance in agriculture. The results identify perceived value to be a decisive mediating function between technology cognition and behavioural intent, highlighting financial and functional utility over conventional TAM measures such as perceived usefulness and ease of use (Davis, 1989; Venkatesh & Davis, 2000). This is in line with existing research that illustrates the importance of perceived value when it comes to adopting agricultural technology (Parmaksiz & Cinar, 2023). In contrast to traditional models, which focus on ease of use, this study highlights the economic feasibility and efficiency as determinants of farmers' adoption behavior (Adekoya et al., 2022).

The results have important practical ramifications for drone manufacturers, agricultural extension agents, and legislators. Awareness campaigns should highlight tangible advantages and cost savings because technological awareness alone does not guarantee acceptance (Rezaei-Moghaddam & Salehi, 2018). Economic incentives, subsidies, and demonstration programs have a significant influence on perceived value and promote adoption, according to empirical data (Michels et al., 2022). Furthermore, since ease of use remains a crucial component for adoption, training programs must prioritise economic viability while addressing perceived complexity (Aydin & Sekerli, 2021).

Mediation analysis is consistent with the fact that perceived value completely mediates the role of technology awareness in intention to use drones, supporting the argument that awareness must be translated into economic and functional advantages for adoption to take place (Waris & Hameed, 2022). Future studies may investigate other variables like perceived risk, trust, and social influence to further develop the adoption model (Singh & Sharma, 2023). The research contributes to the growing literature on the adoption of agricultural technology and offers practical implications for speeding up the use of drones in precision agriculture (Ayamga et al., 2021)..

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