ISSN Print: 2664-6064
ISSN Online: 2664-6072
NAAS Rating (2025): 4.69
IJAN 2025; 7(12): 108-111
www.agriculturejournal.net
Received: 14-10-2025
Accepted: 19-11-2025

Fateh Gadkari
Department of Agricultural Communication, Central Agricultural University, Imphal, Manipur, India

Nitin Tyagi
Department of Agricultural Communication, Central Agricultural University, Imphal, Manipur, India

Bhuvan Gill
Department of Agricultural Communication, Central Agricultural University, Imphal, Manipur, India

Rajeev Ganguly
Department of Extension Education, Chaudhary Charan Singh Haryana Agricultural University, Hisar, Haryana, India

Corresponding Author:
Fateh Gadkari
Department of Agricultural Communication, Central Agricultural University, Imphal, Manipur, India

Farmers willingness to adopt drone technology for pesticide application in rice fields

Fateh Gadkari, Nitin Tyagi, Bhuvan Gill and Rajeev Ganguly

DOI: https://www.doi.org/10.33545/26646064.2025.v7.i12b.520

Abstract
When a rice farmer in Manipur watched a drone spray a neighbour's paddy in under fifteen minutes — a job that normally takes two labourers most of a morning — his first reaction wasn't enthusiasm but scepticism: "That machine can't know where the insects are." This research explored what drives or discourages such farmers from adopting drone-based pesticide application. A structured questionnaire was administered to 240 rice growers across four districts of Manipur and Haryana during 2023. Respondents who had either witnessed or participated in drone demonstrations were categorised as "aware" ($n = 156$); those without exposure as "unaware" ($n = 84$). Perceived usefulness (mean score 4.1/5) and social influence (3.8/5) were the strongest positive predictors of adoption willingness, while cost affordability (2.4/5) and access to technical support (2.9/5) were the primary barriers. Logistic regression showed that farm size, education level, and prior exposure to demonstrations were significant determinants of willingness ($p < 0.01$). These findings suggest that subsidy schemes, community demonstration plots, and after-sales service networks could accelerate drone adoption in Indian rice systems.

Keywords: Drone technology, pesticide application, rice, adoption willingness, precision agriculture, perceived usefulness, extension contact, social influence, technology adoption, Indian agriculture

Introduction
Consider this situation: a small rice farmer in northeast India hires two labourers for half a day to spray insecticide on 0.4 hectares of paddy. The cost is roughly ₹800, the coverage is uneven, and at least one of the workers gets a headache from the chemical drift. Now picture a drone covering the same area in 12 minutes, with uniform droplet distribution and zero human exposure. The technology exists, but the uptake remains low [1].

Agricultural drones for pesticide spraying entered the Indian market around 2018, and government subsidies under the Sub-Mission on Agricultural Mechanization have since reduced unit costs by 40-50% [2]. Yet adoption beyond demonstration plots has been patchy, concentrated among large-scale contract sprayers rather than individual smallholders [3]. Understanding why farmers are willing — or unwilling — to adopt drone spraying is a prerequisite for designing extension strategies that move the technology from pilot to mainstream.

The Technology Acceptance Model (TAM) posits that perceived usefulness and perceived ease of use are the two primary drivers of new-technology adoption [4]. But for agricultural drones, additional factors — cost, social influence from peers, availability of repair services, and risk perception around regulatory restrictions — may matter as much or more [5]. This research assessed these factors among rice growers in Manipur and Haryana, two states with contrasting farm sizes, terrain, and extension infrastructure, to identify actionable levers for accelerating adoption.

Instrument Development and Validation
A structured interview schedule with 42 items was developed based on the extended TAM framework [4]. Items covered six constructs: perceived usefulness (7 items), ease of use (6 items), cost affordability (6 items), social influence (7 items), technical support availability (8 items), and risk perception (8 items). Each item was scored on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). The instrument was validated by a panel of five

extension specialists and pilot-tested on 30 non-sample farmers. Cronbach's alpha for the six constructs ranged from 0.78 to 0.91, indicating acceptable internal consistency [6].

Survey Design and Data Collection

The research was conducted from March to August 2023. Four districts were selected purposively: Imphal East and Thoubal in Manipur, and Karnal and Hisar in Haryana. Sixty farmers per district were chosen by stratified random sampling, stratified by landholding size (marginal: <1 ha; small: 1-2 ha; medium: 2-4 ha; large: >4 ha). Interviews were conducted face-to-face in local languages by trained enumerators. Willingness to adopt was measured as a binary variable (willing / not willing) based on a direct question: "Would you use drone spraying on your rice field if a service provider were available within your block?"

Material and Methods

Material

The sample comprised 240 rice-growing households (120 from Manipur; 120 from Haryana). Of these, 156 farmers had seen at least one drone demonstration (either organised by KVK, a private company, or a fellow farmer), while 84 had no prior exposure. Socio-economic profiles were recorded: age, education (years of schooling), landholding, annual farm income, and extension contact frequency. All data were collected using Android tablets loaded with KoboToolbox, ensuring real-time data quality checks.

Methods

Descriptive statistics summarised farmer profiles and Likert-scale scores by state and awareness category. Construct-level mean scores were compared between willing and unwilling groups using independent-sample t-tests. A binary logistic regression model was fitted with willingness as the dependent variable and six construct scores plus four socio-economic covariates as predictors [7]. Model fit was assessed by the Hosmer-Lemeshow test and Nagelkerke pseudo-R^2. All analyses used SPSS v26.

Results

Table 1: Construct-level mean scores for willing and unwilling farmer groups

Construct	Willing (n=148)	Unwilling (n=92)	t-value (p)
Perceived usefulness	4.12	2.31	8.74 (<0.001)
Ease of use	3.24	2.08	5.63 (<0.001)
Cost affordability	2.41	1.83	3.17 (0.002)
Social influence	3.82	1.97	7.92 (<0.001)
Technical support	2.87	1.62	5.41 (<0.001)
Risk perception	3.48	2.71	3.86 (<0.001)

Scores on 1-5 Likert scale. Higher risk perception score indicates greater concern.

Fig 1: Radar chart comparing construct-level mean scores between willing adopters and reluctant farmers across six dimensions of drone technology perception.

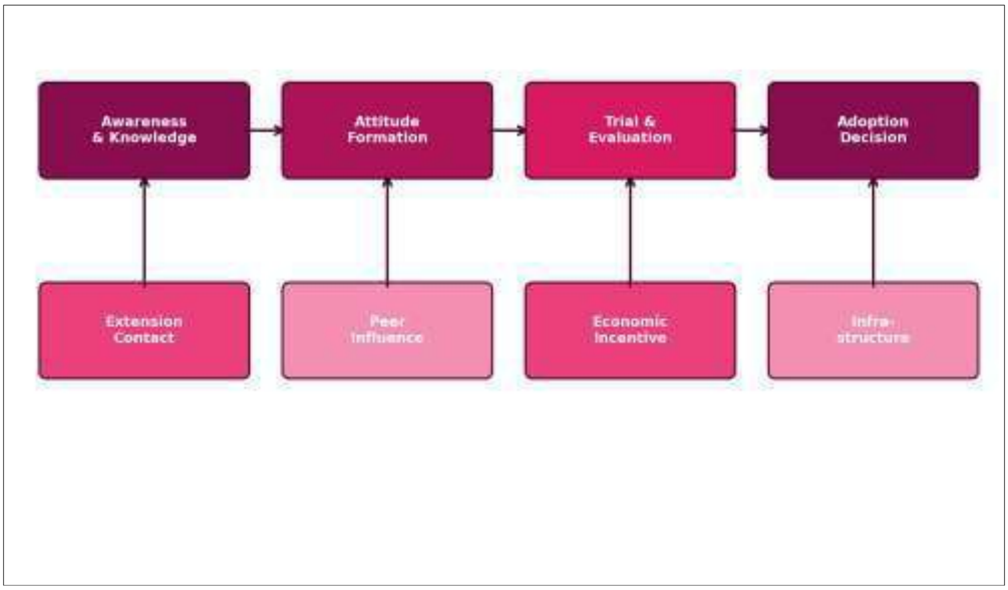

Fig 2: Mechanism diagram illustrating the pathway from awareness to adoption decision, moderated by extension contact, peer influence, economic incentive, and infrastructure availability.

Comprehensive Interpretation

Overall, 61.7% of respondents expressed willingness to adopt drone spraying. Willingness was markedly higher in Haryana (72.5%) than Manipur (50.8%), reflecting Haryana's larger average farm size (3.4 ha vs 0.9 ha) and better access to service providers. In the logistic regression, perceived usefulness (OR = 3.26, $p < 0.001$), farm size (OR = 1.87, $p = 0.004$), and prior demonstration exposure (OR = 2.41, $p = 0.001$) were the strongest positive predictors. Cost affordability had a positive but non-significant effect (OR = 1.23, $p = 0.14$), likely because most farmers envisaged renting rather than owning a drone. The Nagelkerke pseudo-R^2 was 0.58, indicating a reasonably well-fitting model.

Discussion

The dominance of perceived usefulness as an adoption driver mirrors findings from TAM-based studies of agricultural technologies in developing countries [4]. Farmers who had watched a drone spray an entire paddy in minutes grasped the labour-saving potential instantly; those without that visual benchmark remained doubtful. This aligns with Rogers' diffusion theory, where observability and trialability are among the strongest predictors of early adoption [8].

Cost didn't emerge as a statistically significant predictor, which may seem counterintuitive. But the rental model reframes the cost question: at ₹400-500 per acre per spray, drone service is competitive with manual labour in regions where agricultural wages have climbed above ₹350 per day [9]. The real bottleneck is access to service providers, which was reflected in the low technical-support score (2.87 out of 5). For extension agencies, the prescription is clear: invest in live demonstrations (the single strongest lever for shifting attitudes) and support the development of village-level drone service centres. Subsidy design should target service providers rather than individual farmers, building a rental ecosystem that lowers the per-spray cost without requiring each smallholder to own a ₹8-10 lakh machine.

Conclusion

Perceived usefulness and prior demonstration exposure were the strongest drivers of farmers' willingness to adopt drone spraying in rice, while cost affordability and technical-support access were the main barriers. Haryana farmers showed higher willingness than Manipur farmers, linked to larger farm size and better service infrastructure. Extension programmes that prioritise live demonstrations and support drone-service enterprises are likely to be more effective than hardware subsidies aimed at individual farmers.

References

1. Mogili UMR, Deepak BBVL. Review on application of drone systems in precision agriculture. Procedia Comput Sci. 2018;133:502-509.
2. Government of India. Sub-Mission on Agricultural Mechanization operational guidelines. New Delhi: Ministry of Agriculture and Farmers Welfare; 2021. p. 1-42.
3. Murugan D, Garg A, Singh D. Development of an adaptive approach for precision agriculture monitoring with drone and satellite data. IEEE J Sel Top Appl Earth Obs Remote Sens. 2017;10(12):5322-5328.
4. Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q. 1989;13(3):319-340.
5. Khanal S, Fulton J, Klopfenstein A, Douridas N, Shearer S. Integration of high-resolution remotely sensed data and machine learning techniques for spatial prediction of soil properties. Comput Electron Agric. 2018;153:213-225.
6. Nunnally JC, Bernstein IH. *Psychometric theory*. 3rd ed. New York: McGraw-Hill; 1994. p. 1-736.
7. Hosmer DW, Lemeshow S. *Applied logistic regression*. 2nd ed. New York: John Wiley & Sons; 2000. p. 1-375.
8. Rogers EM. *Diffusion of innovations*. 5th ed. New York: Free Press; 2003. p. 1-550.
9. Meena MS, Singh KM, Meena BS. Economics of drone use for agricultural spraying in India. Indian J Ext Educ. 2022;58(1):35-42.
10. Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: toward a unified view. MIS Q. 2003;27(3):425-478.

11. Sinha JP. Aerial robot for smart farming and its acceptability in India. Curr Sci. 2020;118(11):1700-1703.
12. Puri V, Nayyar A, Raja L. Agriculture drones: a modern breakthrough in precision agriculture. J Stat Manag Syst. 2017;20(4):507-518.
13. Kumar A, Mishra B, Sinha B, Rajput VD, Minkina T, Mandzhieva SS. Precision farming technologies for crop protection. Sustainability. 2022;14(3):1688.
14. Raj EFI, Appadurai M, Athiappan K. Precision farming in modern agriculture. Smart Agric Technol. 2022;2:100042.
15. Pathak H, Kumar GAK, Mohapatra SD, Rane J, Jee S. *Drones in agriculture: applications and policy*. Baramati: ICAR-National Institute of Abiotic Stress Management; 2020. p. 1-56.
16. Hunt ER, Daughtry CST. What good are unmanned aircraft systems for agricultural remote sensing and precision agriculture? Int J Remote Sens. 2018;39(15-16):5345-5376.
17. Rejeb A, Abdollahi A, Rejeb K, Treiblmaier H. Drones in agriculture: a review and bibliometric analysis. Comput Electron Agric. 2022;198:107017.
18. Zhou Z, Ming D, Lv J, Zhou Y, Wang M. Unmanned aerial vehicle for crop monitoring in precision agriculture. Adv Mech Eng. 2021;13(6):1-10.