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RECEIVED 29 August 2025

ACCEPTED 31 October 2025

PUBLISHED 28 November 2025

CITATION

Barman B, Singh R, Padaria RN, Nain MS and Quader SW (2025) Modeling determinants of farmers' attitude and adoption willingness toward agricultural drones: a PLS-SEM study in India.
Front. Sustain. Food Syst. 9:1695231.
doi: 10.3389/fsufs.2025.1695231

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Modeling determinants of farmers' attitude and adoption willingness toward agricultural drones: a PLS-SEM study in India

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Agricultural drones represent a rapidly advancing innovation in modern farming, offering significant potential to enhance productivity, optimize input use, reduce labor dependency, and support real-time data-based decision-making. However, despite their proven advantages and increasing market availability, adoption among Indian farmers remains limited. Understanding the factors that shape farmers' attitudes and willingness to adopt drone technology is essential for overcoming barriers and promoting large-scale adoption. This study examines the determinants influencing farmers' attitudes toward agricultural drone technology and their willingness to adopt. A quantitative research approach was adopted, using a structured questionnaire administered to 320 farmers from selected districts in Haryana and Uttar Pradesh, India. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to assess the influence of key predictors on Attitude Toward Technology (ATT). The structural model results indicated that six of the eight hypothesized predictors, Promotional Efforts, Perceived Usefulness, Peer Pressure, Perceived Economic Viability, Perceived Environmental Impact, and Perceived Social Impact, had a statistically significant positive effect on ATT and contributed substantially to explaining variance in adoption willingness. These results reveal that farmer decisions are shaped by psychological, economic, environmental, and social dimensions, rather than purely technical considerations. The study emphasizes that effective adoption strategies must prioritize awareness enhancement, hands-on training, field demonstrations, and financial support mechanisms to improve accessibility and trust. Strengthening institutional support and fostering positive peer experiences could further accelerate technology acceptance among less innovative farmers and later adopters. The findings provide valuable insights for policymakers, extension agencies, and agri-tech developers seeking to scale precision agriculture solutions, positioning agricultural drones as a critical tool for advancing sustainable and technologically enabled farming in India.

KEYWORDS

unmanned aerial vehicles (UAVs), agricultural drones, technology adoption, attitude, willingness to adopt, PLS-SEM

Introduction

The global agricultural landscape is undergoing a profound transformation, driven by the integration of cutting-edge technologies that promise to enhance productivity, sustainability, and resilience (Guebsi et al., 2024). Among these innovations, Unmanned Aerial Vehicles (UAVs), commonly known as drones, are emerging as a revolutionary tool in modern agriculture (Hafeez et al., 2023). Although drones were first created for military logistics and

surveillance, their uses in the civilian sector have grown significantly (Restas, 2015). In the past decade, drone use has rapidly grown in industries like agriculture and commerce, as well as in disaster relief and humanitarian work (Mohd Daud et al., 2022). In agriculture, it offers a range of applications, including crop monitoring, pest control, precision spraying, and real-time data collection. The adoption of such technologies can significantly lead to higher crop yields, resource efficiency, and environmental sustainability (Rejeb et al., 2022). According to the *Agriculture Drone Market Size, Share, Global Forecast (2025)*, the global agricultural drone market is projected to grow from USD 4.98 billion in 2023 to over USD 23.78 billion by 2032.

Drones in agriculture boost productivity, cut costs, enable precise inputs, improve monitoring, detect pests early, and support data-driven decisions (Ayamga et al., 2021; Meivel and Maheswari, 2021; Hafeez et al., 2023). Drones also make it easier to manage large or difficult terrains and help in yield estimation and disaster assessment, supporting crop insurance and farm planning (Benami et al., 2021). However, several challenges limit their global adoption, especially in developing regions (Pathak et al., 2020; Khan et al., 2024), including high costs, regulatory barriers, and data privacy concerns (Rodzi et al., 2024; Puppala et al., 2023). Poor internet connectivity, GPS access in rural areas further hinder their use (Singh et al., 2024; Sangode, 2024; Barman et al., 2025). Additionally, there is a lack of technical knowledge and skilled manpower to operate drones and analyze the data they generate (Singh et al., 2024). Moreover, maintenance and repair challenges, limited access to service centers, and concerns about privacy and data security also discourage farmers (Barnes et al., 2019).

As international agricultural drone regulations continue to change, removing these obstacles will require supportive legislation, capacity building, and cost-effective models. Numerous nations have put in place civil aviation laws that specify no-fly zones, operational restrictions, pilot qualification criteria, and standards for data usage (Mehrotra, 2024). Several Governments as well as organizations like FAO and the World Bank promote agricultural drone adoption through funding, training, and pilot projects, aiming to bridge the digital divide and support smallholder farmers (FAO, 2018).

The global adoption of agricultural drones has witnessed significant growth (Frąckiewicz, 2025). In the United States, drones have become widely integrated into agriculture for crop monitoring, field mapping, and precision spraying, supported by clear regulatory frameworks and advanced technological infrastructure (Global Ag Tech Initiative, 2024). Europe, particularly France, Germany, and the Netherlands, has increasingly adopted agricultural drones to comply with strict environmental regulations and meet precision agriculture objectives (Mordor Intelligence, 2024). In the Asia-Pacific region, China leads drone adoption, significantly driven by government subsidies covering over 150 million acres by 2021 (Ohio State University Extension, 2024). Japan has long integrated drones into its rice farming operations, establishing itself as a mature drone market (Mordor Intelligence, 2024). Meanwhile, Brazil dominates drone usage in Latin America, leveraging the technology extensively in large-scale plantations (Grand View Research, 2024). In Africa, agricultural drone adoption remains at an initial stage, with pilot initiatives in Kenya, Uganda, and Tanzania demonstrating substantial potential for future expansion (WeRobotics, 2024).

India is rapidly scaling up drone usage through government-led initiatives such as the Digital India mission and the Sub-Mission on Agricultural Mechanization, which promote drone adoption via

training programs, financial incentives, and institutional support (Press Information Bureau, 2023). Agriculture, employing about 46% of India's workforce and contributing 18% to GDP, remains vital for food security and rural development (The Times of India, 2024). Agricultural drones have recently emerged as key tools for boosting productivity and precision farming. Recognizing the transformative potential of drone technology in agriculture, the Government of India has launched several promotional initiatives, including the Kisan Drone Scheme under SMAM, offering subsidies up to ₹5 lakh and support for 1,500 Custom Hiring Centers (Press Information Bureau, 2023); the Namo Drone Didi Scheme, aimed at empowering 15,000 women-led SHGs with drones and training; and various state-level programs to expand access, training, and service delivery. Under these schemes, the promotion of agricultural drones is being actively pursued through a combination of extension methods, including financial incentives, on-field demonstrations, hands-on training programs, digital awareness campaigns, and institutional support from ICAR, KVKs, SAUs, and state agriculture departments. This multi-pronged approach aims to enhance awareness, build technical capacity, and reduce economic and operational barriers to encourage widespread adoption of drone technology among Indian farmers. Despite these efforts, adoption remains modest due to affordability issues, limited technical skills, and infrastructural gaps, stressing the urgent need to explore the underlying factors influencing farmers' willingness to adopt drone technology.

Exploring Indian farmers' willingness to adopt drones is thus timely and essential. This study provides valuable insights into the effectiveness of ongoing policy initiatives, sheds light on socio-economic and practical barriers affecting technology uptake, and assists policymakers, technology developers, and agricultural stakeholders in refining strategies for better implementation. Ultimately, such insights can enhance the efficacy of public investments in drone technology, driving tangible improvements in agricultural productivity, sustainability, and the livelihoods of millions of Indian farmers.

Key applications of drones in agriculture

Drones are transforming global agriculture through a wide array of applications that enhance productivity, sustainability, and efficiency. As shown in Table 1, drones have various major applications in agriculture. In crop surveillance and health monitoring, drones equipped with multispectral and thermal sensors enable early detection of plant stress, pest attacks, and nutrient deficiencies, allowing farmers to take timely corrective measures. Precision spraying, guided by GPS, allows drones to apply fertilizers, pesticides, and herbicides with remarkable accuracy, reducing chemical usage by up to 30% while minimizing environmental contamination and protecting workers from exposure (Guebsi et al., 2024). In challenging terrains, drones are also used for planting and seeding, particularly in reforestation and conservation efforts. Additionally, drones support field mapping and data analytics by capturing high-resolution imagery and creating 3D maps that highlight soil variability, water flow, and elevation, enabling optimized input use and smarter farm management (Mogili and Deepak, 2018). For yield estimation, drones assess crop vigor and canopy structure to forecast production levels, while also serving as critical tools in crop insurance by quickly and accurately

TABLE 1 Major agricultural applications of drones.

Application	Description
Crop Monitoring	Drones equipped with multispectral sensors provide real-time data on plant health, detecting pests, diseases, and nutrient deficiencies before they become visible.
Precision Spraying	Drones spray fertilizers, pesticides, and herbicides with high precision, reducing input waste and minimizing chemical runoff.
Field Mapping and Planning	Drones capture high-resolution imagery to create detailed maps, helping farmers assess soil variability, terrain, and water management.
Yield Estimation	Drones use sensors to estimate crop yield by analyzing plant vigor, canopy size, and biomass, assisting in harvest planning and crop insurance.
Planting and Seeding	Specialized drones can plant seeds and cover crops in areas that are difficult to reach with traditional machinery, enhancing productivity.
Livestock Monitoring	Drones are used to monitor livestock movement, track animal health, and inspect pastures or fences, improving overall farm management.
Disaster and Damage Assessment	In case of natural disasters, drones are used to quickly assess crop damage, enabling faster insurance claims and recovery.
Irrigation Monitoring	Drones equipped with thermal sensors monitor soil moisture levels, helping optimize irrigation practices and prevent water wastage.
Environmental Monitoring	Drones are used for biodiversity and environmental monitoring, helping track changes in ecosystems, soil health, and water resources.

Sources: Kumar et al. (2023), García-Munguía et al. (2024), and Ahirwar et al. (2019).

documenting post-disaster damage. Beyond crops, drones contribute to livestock management by monitoring herd movements, checking for fencing breaches, and identifying threats, significantly reducing labor and time in large-scale livestock operations.

Importance of agricultural drones in Indian farming

Agriculture in India is undergoing a paradigm shift with the integration of emerging technologies aimed at enhancing productivity, reducing input costs, and ensuring environmental sustainability. Among these innovations, agricultural drones, also known as Unmanned Aerial Vehicles (UAVs), are gaining prominence for their ability to perform real-time crop monitoring, precision spraying, soil health mapping, plant disease detection, and yield estimation. These capabilities can significantly improve input-use efficiency, reduce manual labor dependency, and facilitate timely agricultural interventions, particularly in large and medium-scale farming operations. However, the adoption of drone technology in Indian agriculture remains in its nascent stages, especially among small and marginal farmers who constitute nearly 86% of the farming community (Agricultural Census, 2015–16). The high cost of drones, limited awareness, inadequate technical skills, and risk perception act as major barriers. In this context, promotional efforts by the government, private sector, and agricultural extension agencies become critical to influence farmers’ willingness and ability to adopt such innovations.

To bridge the gap between technology availability and on-ground adoption, the Government of India has introduced several promotional schemes and policy frameworks (PIB, 2022) aimed at creating an enabling ecosystem for drone usage in agriculture:

- **Kisan Drone Scheme:** Launched under the Ministry of Agriculture and Farmers Welfare, this initiative promotes the use

of drones for various agricultural purposes. Financial assistance is provided for the purchase of drones by farmer-producer organizations (FPOs), cooperative societies, and custom hiring centers (CHCs).

- **Drone Shakti Initiative:** Announced to encourage drone startups and facilitate ‘Drone-as-a-Service’ (DaaS), the initiative aims to build a robust ecosystem by promoting entrepreneurship and local drone manufacturing.
- **Drone Didi Yojana:** Launched under the aegis of the Lakhpati Didi initiative, this scheme empowers rural women by training them to operate agricultural drones and provide drone services within their communities. It aims to create 15,000 women drone pilots, offering both skill development and entrepreneurial opportunities.
- **Sub-Mission on Agricultural Mechanization (SMAM):** Offers 40–100% subsidies for the purchase of agricultural drones and related equipment by eligible entities, especially in aspirational districts and for Scheduled Castes/Scheduled Tribes and women farmers.
- **Custom Hiring Centres (CHCs):** These centers are supported under various schemes to offer drone services to smallholders who cannot afford to buy drones individually, thereby promoting shared access and affordability.
- **Digital Agriculture Mission:** A broader initiative that includes the promotion of emerging technologies such as AI, blockchain, and drones for digital transformation in agriculture.

In addition to government interventions, private companies and agritech startups are also actively engaging in awareness creation, field demonstrations, pilot programs, and influencer-based campaigns to promote drone usage. Extension agencies and Krishi Vigyan Kendras (KVKs) are organizing on-field training, exhibitions, and capacity-building sessions for farmers and rural youth.

Conceptual framework

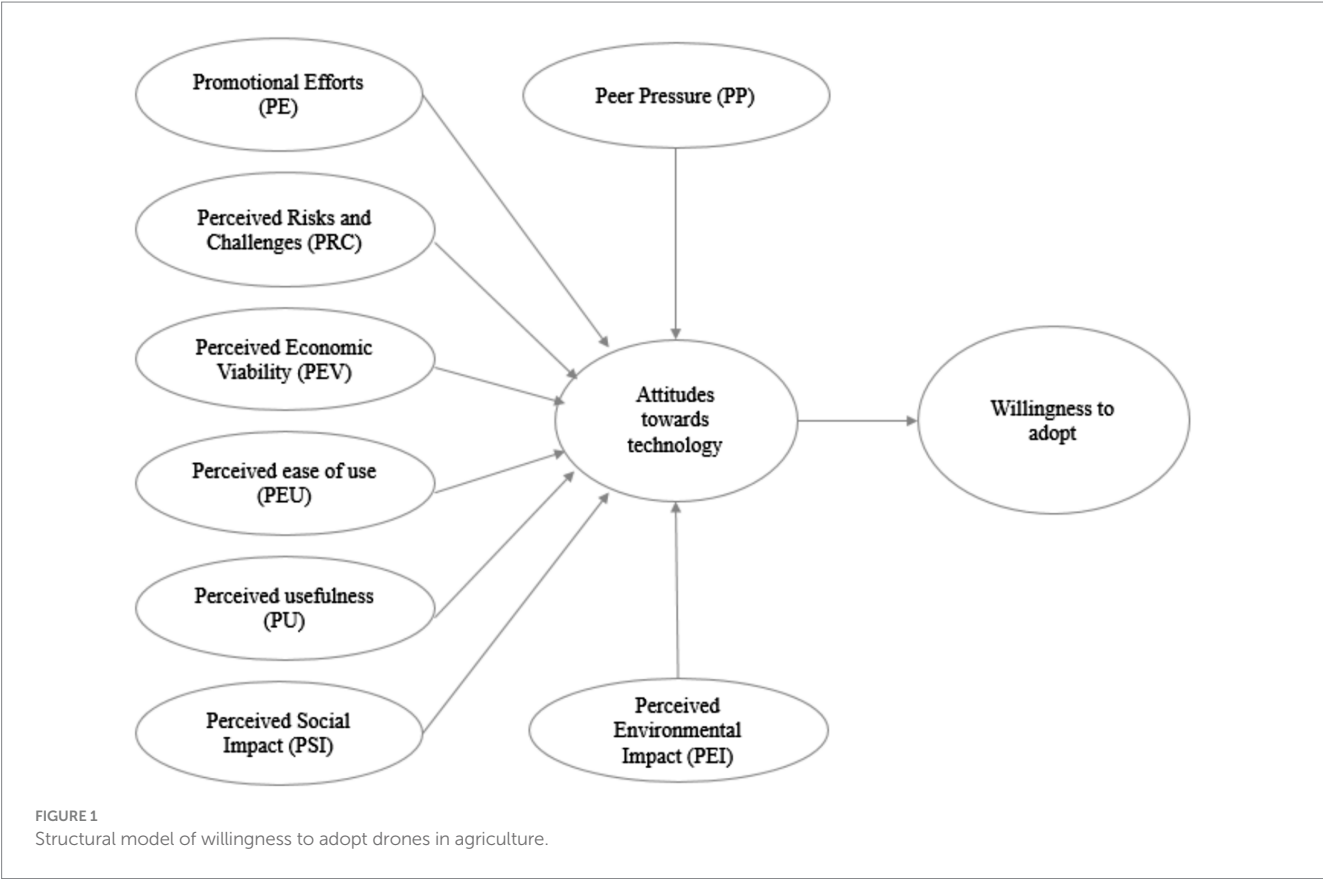
One of the most widely applied theoretical models for understanding technology adoption is the Technology Acceptance Model (TAM), which posits that perceived usefulness and perceived ease of use are crucial determinants of technology acceptance (Davis, 1989; Davis and Granić, 2024). While TAM has been extensively applied in various domains, its application in the Indian agricultural context, particularly to agricultural drones, requires contextual adaptation. Indian farmers, especially small and marginal holders, often face additional constraints such as limited access to capital, fragmented landholdings, and varying levels of digital literacy. Therefore, understanding drone adoption necessitates expanding TAM to include factors like Perceived Economic Viability (PEV), Perceived Environmental Impact (PEI), Perceived Social Impact (PSI), Perceived Risks and Challenges (PRC), and Peer Pressure (PP), all of which are highly relevant in rural India (Figure 1). Moreover, in India, where government-led promotional schemes like the Kisan Drone Scheme and Drone Didi Yojana are actively promoting drone technology, promotional efforts (PE) such as financial subsidies, capacity-building training, demonstrations, and digital campaigns play a crucial role.

Relevance of key factors in the Indian context for agricultural drone adoption

In the Indian context, where agriculture remains the primary livelihood for millions of rural households, understanding the

determinants of technology adoption is crucial, especially for emerging innovations like agricultural drones. The following is an overview of the key factors relevant to agricultural drones within the Indian farming context.

- a) *Perceived usefulness (PU)*: Perceived usefulness refers to the extent to which farmers believe that using drone technology will enhance their agricultural performance (Caffaro et al., 2020). In the Indian context, farmers frequently face fragmented landholdings, labor shortages, high input costs, and inefficiencies in input application (Manjunatha et al., 2013; Deininger et al., 2017). Agricultural drones offer a practical solution by enabling precise spraying, timely monitoring, and crop health assessments through remote sensing. These functions can lead to increased productivity, improved pest and disease management, and ultimately higher yields (Guebsi et al., 2024). When farmers perceive drones as beneficial tools that reduce effort and enhance outcomes, their willingness to adopt the technology increases significantly (McCarthy et al., 2023). This is particularly relevant in areas where traditional farming practices are becoming less efficient due to climate variability or resource constraints.
- b) *Perceived ease of use (PEU)*: Ease of use is a critical determinant of technology adoption in rural India, where digital literacy and exposure to high-tech solutions remain limited, particularly among small and marginal farmers (Manrai et al., 2021; Sindakis and Showkat, 2024; Lahiri et al., 2024). If drones are perceived as complex, difficult to operate, or requiring specialized skills, farmers may hesitate to adopt them regardless



of their potential benefits (Caffaro et al., 2020). This is compounded by barriers such as a lack of technical support in local regions and limited access to repair or maintenance services. However, if drones are designed to be user-friendly or accompanied by accessible training programs such as those provided under the *Kisan Drone Scheme* and by KVKs, then even digitally inexperienced farmers are more likely to accept and adopt the technology.

- c) *Perceived economic viability (PEV)*: Economic viability plays a vital role in farmers' decision-making processes, especially in India, where over 85% of farmers are classified as small and marginal (Namara et al., 2007; Mittal and Mehar, 2016). These farmers often operate on tight budgets and are highly sensitive to capital expenditure and operational costs. Drones, despite their long-term benefits, involve significant upfront investment. Suppose farmers perceive that drone adoption will lead to tangible cost savings through reduced input wastage, fewer labor requirements, or better pest control. In that case, they are more likely to consider the investment worthwhile. Additionally, the availability of financial support mechanisms such as subsidies (e.g., up to 50% under the *Kisan Drone Scheme*) and Custom Hiring Centers (CHCs) greatly influences perceptions of affordability and return on investment.
- d) *Perceived risks and challenges (PRC)*: Indian farmers often operate in risk-prone environments due to dependency on monsoons, market price volatility, and socio-economic uncertainty (Jewitt and Baker, 2012; Mandal et al., 2021). Introducing a new technology like drones adds another layer of perceived risk. Farmers may worry about technical failures, accidents, regulatory issues, and a lack of servicing infrastructure in rural areas. Moreover, concerns about drone piloting skills, data privacy, or compliance with government regulations may also act as deterrents. If these challenges are not addressed through institutional support, awareness programs, and confidence-building demonstrations, farmers may perceive the risks as outweighing the benefits, thus hindering adoption.
- e) *Perceived social impact (PSI)*: Social impact in rural Indian communities is a significant influencing factor in the adoption of new technologies (Tambotih et al., 2015; Ray et al., 2019). If drones are viewed as beneficial not only to the individual farmer but also to the larger community by improving health through reduced chemical exposure, saving time for other livelihood activities, or enhancing prestige and social standing, then the technology is more likely to be embraced. Furthermore, the collective nature of Indian villages often leads to group decision-making, where social norms, cultural acceptance, and collective benefit play a pivotal role in influencing individual choices (Mosse, 2006; Trivedi et al., 2024; Voorhaar et al., 2025).
- f) *Perceived environmental impact (PEI)*: There is growing awareness among Indian farmers, particularly those involved in organic or climate-resilient agriculture, about the importance of sustainable farming practices (Rahman, 2005; Guo et al., 2022). Drones, by enabling precision application of fertilizers and pesticides, can minimize environmental degradation, protect biodiversity, and conserve water and soil health. If farmers recognize these ecological advantages, drones are more likely to be accepted not just as a productivity tool but as part of a sustainable farming model.
- g) *Peer pressure (PP)*: In India, peer influence remains a powerful factor in technology diffusion, especially in rural settings where community leaders, progressive farmers, or early adopters serve as opinion leaders (Kim et al., 2007; Negi et al., 2022). Farmers often consult neighbors or local influencers before investing in unfamiliar technologies. If they see others in their village successfully using drones, it creates a bandwagon effect, increasing their own interest and trust in the technology. On the contrary, if influential peers express skepticism or report negative experiences, it may deter adoption. Thus, peer endorsement, especially when supported by extension workers or demonstration plots, can play a crucial role in shaping attitudes and behavior.
- h) *Attitude toward technology (ATT)*: Attitude is a central psychological construct in the adoption process (Davis, 1989; Davis and Granić, 2024). In the Indian agricultural context, a farmer's attitude toward new technology is shaped by prior experiences, perceived relevance, cultural openness to innovation, and trust in government or institutional interventions. A positive attitude, fostered through exposure to successful use cases, training sessions, or incentives, enhances a farmer's readiness to try and eventually adopt drone technology. Negative attitudes, on the other hand, may stem from previous failed interventions, lack of institutional support, or perceived exclusion from technological advancement.
- i) *Promotional Efforts (PE)*: Promotional efforts in India, spearheaded by central and state governments, NGOs, and private agri-tech firms, play a significant role in shaping perceptions and reducing adoption barriers (Hiranya and Joshi, 2025; Vasavi et al., 2025). These efforts include financial incentives (such as subsidies under the *Kisan Drone Scheme*), demonstrations and field days organized by KVKs, training and capacity-building programs, digital awareness campaigns, and institutional support through schemes like the *Drone Didi Yojana*. Such interventions not only inform farmers about drone benefits but also reduce uncertainty and build technical confidence. Promotional efforts act as an important factor, strengthening the relationship between farmers' positive perceptions and their actual willingness to adopt (Li et al., 2021; Han et al., 2022; Luo et al., 2022).
- j) *Willingness to adopt (WA)*: Willingness to adopt, often referred to as symbolic adoption (Karahanna and Agarwal, 2006), represents the outcome variable in the adoption framework, reflecting a farmer's intention or readiness to embrace drone technology in agricultural practices (Davis, 1989; Davis and Granić, 2024). In the Indian context, this willingness is influenced by a combination of technical, economic, social, and institutional factors. Beyond the perceived usefulness and ease of use of the technology, Indian farmers evaluate whether drone adoption aligns with their existing farming systems, landholding size, crop types, and socio-cultural values. Moreover, trust in the promoting institutions, such as government agencies, Krishi Vigyan Kendras (KVKs), or local extension services, plays a vital role in shaping this intent. Farmers are more inclined to adopt when they perceive drone technology as low-risk, socially

acceptable, economically viable, and supported by credible institutions. A high degree of willingness, therefore, signals a readiness to move from mere awareness to actual behavioral adoption. Understanding the determinants of this symbolic adoption is crucial for policymakers, technology developers, and extension agents, as it offers practical insights into how to convert farmer interest into real-world usage, ultimately enhancing the reach, impact, and sustainability of drone interventions in Indian agriculture.

Based on the conceptual framework, the study proposes the following hypotheses:

H1: Perceived Usefulness (PU) positively affects farmers' Attitude Toward Technology (ATT).

H2: Perceived Ease of Use (PEU) positively affects farmers' Attitude Toward Technology (ATT).

H3: Perceived Economic Viability (PEV) positively affects farmers' Attitude Toward Technology (ATT).

H4: Perceived Risks and Challenges (PRC) negatively affect farmers' Attitude Toward Technology (ATT).

H5: Perceived Social Impact (PSI) positively affects farmers' Attitude Toward Technology (ATT).

H6: Perceived Environmental Impact (PEI) positively affects farmers' Attitude Toward Technology (ATT).

H7: Peer Pressure (PP) positively affects farmers' Attitude Toward Technology (ATT).

H8: Promotional Efforts (PE) positively affect farmers' Attitude Toward Technology (ATT).

H9: Attitude Toward Technology (ATT) positively affects farmers' Willingness to Adopt (WA) agricultural drones.

Methodology

The study was conducted in Haryana and Uttar Pradesh, where drone-based agricultural practices are actively promoted. A multi-stage purposive-cum-random sampling technique was adopted. First, two districts were selected from each state based on drone usage intensity. Then, two blocks from each district were chosen purposively. From each block, 80 respondents were randomly selected, resulting in a total sample size of 320 respondents.

Data collection and data analysis

A structured questionnaire was developed based on existing literature and validated through expert consultation. The questionnaire included the following constructs, each measured

using multiple items on a 7-point Likert scale (1 = Strongly Disagree to 7 = Strongly Agree). Data were collected through face-to-face interviews using a pre-tested structured schedule. Data were analyzed using R in the PLS-PM Package (Sanchez, 2013; Sanchez et al., 2014). To test the measurement model, Confirmatory Factor Analysis (CFA) was conducted to assess construct reliability, convergent validity, and discriminant validity. The hypothesized relationships among variables were examined using Partial Least Squares Structural Equation Modeling (PLS-SEM). The mediating role of Attitude Toward Technology (ATT) was tested using the bootstrapping technique.

The study's conceptual framework involves multiple latent constructs such as Perceived Usefulness (PU), Perceived Ease of Use (PEU), Perceived Economic Viability (PEV), Perceived Risks and Challenges (PRC), Perceived Social Impact (PSI), Perceived Environmental Impact (PEI), Peer Pressure (PP), Promotional Efforts (PE), Attitude Toward Technology (ATT), and Willingness to Adopt (WA) that are measured through survey items. SEM is suitable because it allows simultaneous estimation of relationships between these latent variables, capturing direct, indirect, and total effects, which is essential for testing all nine proposed hypotheses (Fan et al., 2016). CB-SEM is appropriate if the goal is to confirm the theoretical relationships specified in the framework and if the data meet assumptions of normality and large sample size, while PLS-SEM is suitable for predictive and exploratory analysis, especially if the sample is smaller, data are non-normal, or the focus is on explaining the variance in farmers' adoption intention (Dash and Paul, 2021). Therefore, SEM provides a rigorous statistical approach to validate the framework and understand the key drivers of farmers' attitudes and adoption of agricultural drones.

The study employed PLS-SEM to examine the relationships among latent constructs such as Perceived Usefulness (PU), Perceived Ease of Use (PEU), Perceived Economic Viability (PEV), Perceived Risks and Challenges (PRC), Perceived Social and Environmental Impact (PSI, PEI), Peer Pressure (PP), Promotional Efforts (PE), Attitude Toward Technology (ATT), and Willingness to Adopt (WA). PLS-SEM was chosen because it is particularly suitable for predictive and exploratory research, and allows for handling complex models with multiple constructs and mediators. It enables the estimation of direct, indirect, and total effects, making it ideal for testing the nine proposed hypotheses and identifying the key factors influencing farmers' attitudes and adoption of agricultural drones (Hair et al., 2017).

Results

Construct reliability and convergent validity

To assess the internal consistency, construct reliability, and convergent validity of the latent constructs, several psychometric properties were examined, including Cronbach's alpha (α), DG rho, Average Variance Extracted (AVE), and eigenvalues from exploratory factor analysis (Table 2). All constructs demonstrated excellent internal consistency, with Cronbach's alpha values ranging from 0.975 (Peer Pressure) to 0.989 (Perceived Ease of

TABLE 2 Construct reliability and convergent validity.

Construct	Items	Cronbach's α	DG rho	AVE	First eigenvalue	Second eigenvalue
PEU	8	0.989	0.990	0.928	7.42	0.106
PE	5	0.980	0.985	0.928	4.64	0.099
PU	5	0.980	0.984	0.926	4.63	0.107
PEI	5	0.977	0.982	0.916	4.58	0.124
PP	4	0.975	0.981	0.930	3.72	0.114
PEV	5	0.979	0.983	0.922	4.61	0.109
PSI	4	0.977	0.983	0.934	3.74	0.103
PRC	5	0.983	0.986	0.936	4.68	0.099
ATT	5	0.977	0.982	0.916	4.58	0.126
WA	5	0.985	0.988	0.942	4.71	0.088

Use), all exceeding the recommended threshold of 0.70 (Sobaih and Elshaer, 2022). Similarly, DG rho values were consistently high, ranging from 0.981 to 0.990, confirming strong construct reliability. Convergent validity was verified through AVE values, which ranged from 0.916 to 0.942, well above the 0.50 threshold, indicating that the indicators strongly converge on their respective constructs. Further, the unidimensionality of each construct was supported by the results of principal component analysis, where the first eigenvalue in each case was substantially larger than the second eigenvalue, which remained below 0.13. For instance, Perceived Ease of Use had a first eigenvalue of 7.42 and a second eigenvalue of only 0.106, indicating clear unidimensionality and minimal risk of multidimensionality.

These findings collectively affirm that all constructs used in the model demonstrate strong reliability and validity, supporting their suitability for subsequent structural model analysis.

Outer model results

To further validate the measurement model, the outer weights, loadings, communalities, and redundancies of each indicator were assessed (Table 3). All indicators across constructs exhibited very high loadings, ranging from 0.953 to 0.973, indicating strong relationships between indicators and their respective latent constructs (Hair et al., 2017). The corresponding communalities (squared loadings) were all above 0.90, affirming that a substantial proportion of variance in each item was explained by the construct it measured.

For example, within the Perceived Ease of Use (PEU) construct, item loadings ranged from 0.958 to 0.968, with corresponding communalities between 0.919 and 0.937. Similarly, items under Perceived Usefulness (PU) showed loadings between 0.959 and 0.967, and communalities from 0.920 to 0.936. All constructs maintained balanced outer weights, reflecting the relative contribution of each indicator to the formative score. For instance, the Peer Pressure (PP) indicators had weights ranging from 0.204 to 0.214, and similar patterns were observed across other blocks. Redundancy values for all constructs except the endogenous variables (ATT and WA) were zero, consistent with expectations in

reflective measurement models without endogenous outcomes. For the constructs Attitude Toward Technology (ATT) and Willingness to Adopt (WA), redundancy values ranged from 0.680 to 0.689 and 0.596 to 0.605, respectively, indicating a moderate level of predictive relevance from the structural model. These results confirm strong indicator reliability, internal consistency, and measurement validity, justifying the use of these constructs in the structural path model.

Discriminant validity

The inter-construct correlations were examined to assess the strength and direction of linear relationships among latent variables (Table 4). All constructs demonstrated strong and positive correlations, indicating conceptual coherence and potential theoretical relevance in the structural model (Leguina, 2015).

The strongest correlation was observed between Perceived Ease of Use (PEU) and Perceived Risks and Challenges (PRC) ($r = 0.984$), suggesting a high degree of shared variance. Similarly, strong correlations existed between PEU and WA ($r = 0.803$), PEU and PP ($r = 0.799$), and PEV and WA ($r = 0.807$), implying that ease of use, peer influence, and economic viability are influential drivers of willingness to adopt. Attitude Toward Technology (ATT) also showed consistently strong correlations with its hypothesized predictors, including PU ($r = 0.775$), PE ($r = 0.784$), PP ($r = 0.783$), and PEV ($r = 0.776$), supporting the model's theoretical assumptions. The correlation between ATT and WA ($r = 0.799$) further confirmed that a favorable attitude substantially influences adoption intentions. All inter-construct correlations remained below 0.985, indicating an acceptable level of discriminant validity (Schamberger, 2023). While PEU and PRC were highly correlated, their AVE values and loadings were sufficiently distinct, minimizing the risk of multicollinearity.

Structural model evaluation

The hypothesized relationships among the latent constructs were tested using Partial Least Squares Structural Equation Modeling (PLS-SEM). Table 5 and Figure 2 present the standardized

TABLE 3 Outer model results.

Block	Indicator	Weight	Loading	Communality	Redundancy
PEU	PE1	0.128	0.958	0.919	0.000
	PE2	0.129	0.963	0.928	0.000
	PE3	0.131	0.963	0.928	0.000
	PE4	0.131	0.963	0.928	0.000
	PE5	0.130	0.961	0.923	0.000
	PE6	0.129	0.963	0.928	0.000
	PE7	0.129	0.965	0.932	0.000
	PE8	0.131	0.968	0.937	0.000
PE	PEU1	0.208	0.962	0.925	0.000
	PEU2	0.211	0.962	0.926	0.000
	PEU3	0.206	0.965	0.930	0.000
	PEU4	0.207	0.966	0.933	0.000
	PEU5	0.206	0.961	0.923	0.000
PU	PU1	0.209	0.967	0.936	0.000
	PU2	0.211	0.963	0.928	0.000
	PU3	0.202	0.961	0.923	0.000
	PU4	0.206	0.959	0.920	0.000
	PU5	0.212	0.960	0.922	0.000
PEI	PP1	0.204	0.955	0.911	0.000
	PP2	0.211	0.961	0.924	0.000
	PP3	0.206	0.953	0.907	0.000
	PP4	0.214	0.955	0.912	0.000
	PP5	0.210	0.962	0.926	0.000
PP	PRC1	0.262	0.968	0.936	0.000
	PRC2	0.256	0.963	0.927	0.000
	PRC3	0.262	0.967	0.934	0.000
	PRC4	0.257	0.960	0.922	0.000
PEV	PSI1	0.206	0.961	0.924	0.000
	PSI2	0.211	0.963	0.927	0.000
	PSI3	0.209	0.960	0.922	0.000
	PSI4	0.207	0.958	0.917	0.000
	PSI5	0.208	0.959	0.920	0.000
PSI	PEI1	0.262	0.970	0.942	0.000
	PEI2	0.257	0.964	0.929	0.000
	PEI3	0.259	0.969	0.939	0.000
	PEI4	0.257	0.963	0.928	0.000
PRC	PEV1	0.207	0.968	0.938	0.000
	PEV2	0.203	0.968	0.937	0.000
	PEV3	0.208	0.971	0.944	0.000
	PEV4	0.207	0.967	0.936	0.000
	PEV5	0.209	0.962	0.925	0.000

(Continued)

TABLE 3 (Continued)

Block	Indicator	Weight	Loading	Communality	Redundancy
ATT	ATT1	0.208	0.958	0.918	0.687
	ATT2	0.211	0.954	0.910	0.680
	ATT3	0.209	0.960	0.921	0.689
	ATT4	0.210	0.959	0.920	0.688
	ATT5	0.207	0.953	0.909	0.680
WA	WA1	0.205	0.973	0.947	0.605
	WA2	0.206	0.972	0.945	0.604
	WA3	0.207	0.966	0.933	0.596
	WA4	0.206	0.972	0.945	0.603
	WA5	0.206	0.969	0.940	0.600

TABLE 4 Correlations among latent variables.

Construct	PEU	PE	PU	PEI	PP	PEV	PSI	PRC	ATT	WA
PEU	1.000									
PE	0.784	1.000								
PU	0.777	0.769	1.000							
PEI	0.747	0.757	0.740	1.000						
PP	0.799	0.755	0.770	0.749	1.000					
PEV	0.792	0.789	0.760	0.729	0.782	1.000				
PSI	0.791	0.778	0.767	0.741	0.789	0.764	1.000			
PRC	0.984	0.780	0.773	0.752	0.789	0.784	0.786	1.000		
ATT	0.773	0.784	0.775	0.750	0.783	0.776	0.770	0.770	1.000	
WA	0.803	0.788	0.774	0.764	0.763	0.807	0.773	0.802	0.799	1.000

TABLE 5 Path coefficients and significance.

Path	Original β	Boot mean	Std. error	95% CI (2.5, 97.5%)	p -value	Sig
PEU $\rightarrow$ ATT	0.0068	0.00454	0.1551	[−0.2981, 0.308]	0.967	NS
PE $\rightarrow$ ATT	0.1741	0.17650	0.0644	[0.0512, 0.304]	0.002	**
PU $\rightarrow$ ATT	0.1591	0.15925	0.0561	[0.0493, 0.269]	0.004	**
PEI $\rightarrow$ ATT	0.1217	0.12022	0.0484	[0.0222, 0.215]	0.017	*
PP $\rightarrow$ ATT	0.1688	0.16861	0.0542	[0.0602, 0.273]	0.003	**
PEV $\rightarrow$ ATT	0.1439	0.14488	0.0531	[0.0408, 0.247]	0.010	**
PSI $\rightarrow$ ATT	0.1118	0.11053	0.0630	[−0.0141, 0.230]	0.047	*
PRC $\rightarrow$ ATT	0.0797	0.08154	0.1531	[−0.2204, 0.386]	0.618	NS
ATT $\rightarrow$ WA	0.7992	0.79936	0.0213	[0.7541, 0.838]	<0.001	***

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, NS, Not significant.

path coefficients (β), bootstrapped standard errors, 95% confidence intervals, and p -values obtained through 5,000 bootstrap resamples (Streukens and Leroi-Werelds, 2016; Magno et al., 2024).

Among the exogenous constructs predicting Attitude Toward Technology (ATT), six demonstrated statistically significant positive effects. Specifically, Promotional Efforts (PE) exerted a significant influence on ATT ($\beta = 0.1741$, $p = 0.002$), followed by Perceived Usefulness (PU) ($\beta = 0.1591$, $p = 0.004$), Perceived Environmental Impact (PEI) ($\beta = 0.1217$, $p = 0.017$), Peer

Pressure (PP) ($\beta = 0.1688$, $p = 0.003$), and Perceived Economic Viability (PEV) ($\beta = 0.1439$, $p = 0.010$). Additionally, Perceived Social Impact (PSI) was marginally significant ($\beta = 0.1118$, $p = 0.047$), indicating a positive yet relatively weaker effect on ATT.

In contrast, the paths from Perceived Ease of Use (PEU) ($\beta = 0.007$, $p = 0.967$) and Perceived Risks and Challenges (PRC) ($\beta = 0.0797$, $p = 0.618$) to ATT were found to be statistically non-significant. This suggests that these factors did not substantially

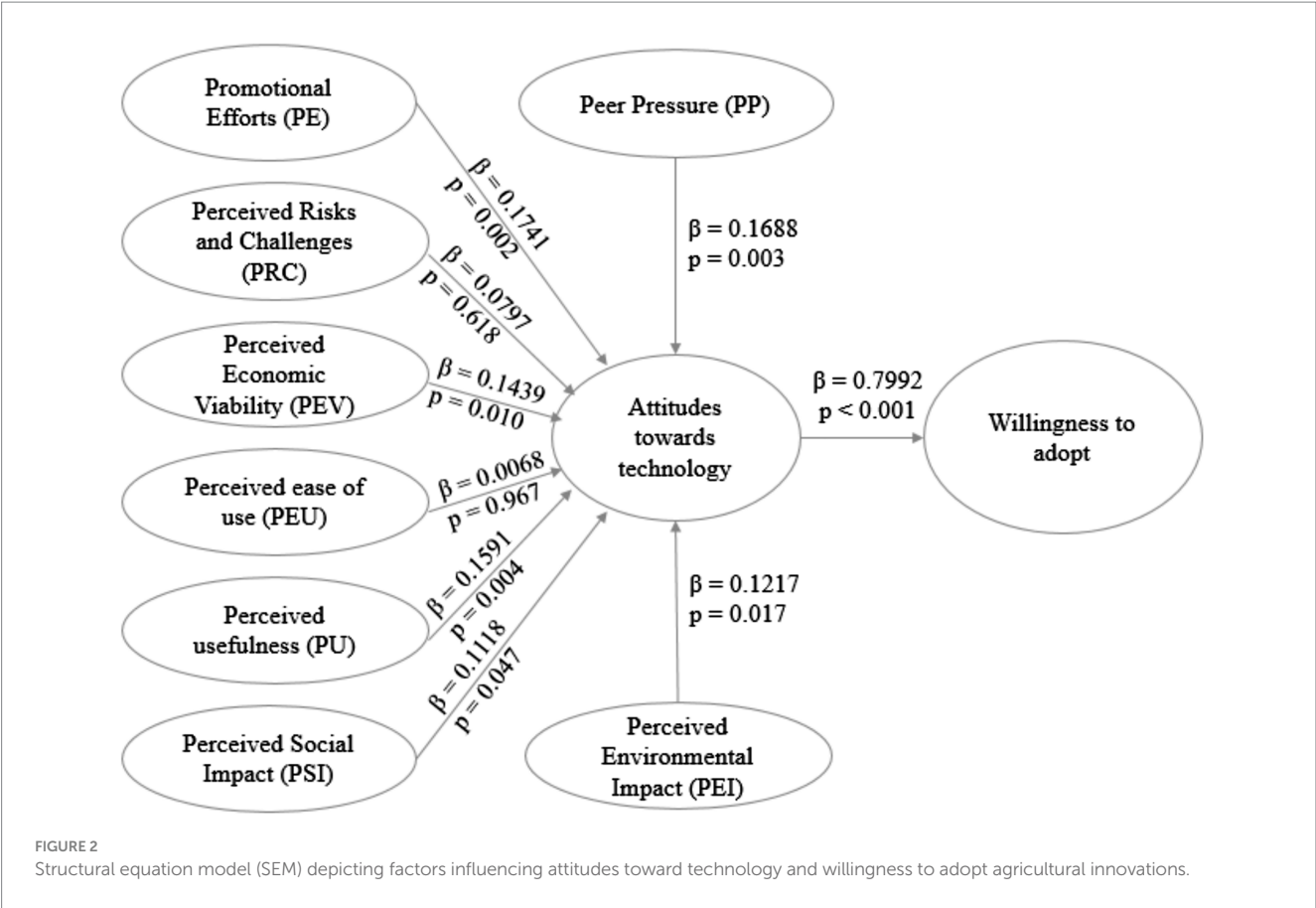


TABLE 6 Coefficient of determination (R^2).

Endogenous variable	R^2 (Original)	Boot mean	Std. error	95% CI (2.5, 97.5%)
ATT	0.748	0.754	0.0242	[0.705, 0.799]
WA	0.639	0.639	0.0339	[0.569, 0.703]

contribute to shaping attitudes toward the adoption of agricultural drone technology within the present context.

Importantly, Attitude Toward Technology (ATT) was a strong and significant predictor of Willingness to Adopt (WA) ($\beta = 0.7992$, $p < 0.001$), supporting its mediating role within the theoretical framework.

R^2 and variance explained

The explanatory power of the structural model was assessed using the coefficient of determination (R^2) values for the endogenous constructs. As presented in Table 6, the model explained a substantial proportion of variance in both Attitude Toward Technology (ATT) and Willingness to Adopt (WA).

The R^2 value for ATT was 0.748, indicating that approximately 74.8% of the variance in attitude toward technology was explained by its antecedent constructs (Chin, 1998). The bootstrapped 95% confidence interval [0.705, 0.799] confirmed the robustness and reliability of this estimate (Schamberger, 2023).

Similarly, the R^2 value for WA was 0.639, suggesting that 63.9% of the variance in willingness to adopt agricultural drone technology was accounted for by ATT. The bootstrapped confidence interval [0.568, 0.700] further validated the predictive accuracy of the model.

According to established benchmarks (Hair et al., 2017), these R^2 values can be considered substantial (for ATT) and moderate to substantial (for WA), indicating a strong model fit and a high level of explanatory relevance for technology adoption behavior in the agricultural context.

PLS path model results

The total effects analysis in Table 7 revealed that Attitude Toward Technology (ATT) had the most substantial impact on Willingness to Adopt (WA) ($\beta = 0.799$, 95% CI [0.753, 0.836], $p < 0.001$), underscoring its central mediating role in the model (Guenther et al., 2023). Several exogenous constructs exerted significant indirect effects on WA through ATT, including Promotional Efforts (PE) ($\beta = 0.139$, $p < 0.01$), Perceived Usefulness (PU) ($\beta = 0.127$, $p < 0.01$), Peer Pressure (PP) ($\beta = 0.135$, $p < 0.01$), Perceived Economic Viability (PEV) ($\beta = 0.115$, $p < 0.05$), and Perceived Environmental Impact (PEI) ($\beta = 0.097$, $p < 0.05$). However, the total effects of Perceived Ease of Use (PEU), Perceived Social Impact (PSI), and Perceived Risks and Challenges (PRC) were not statistically significant, suggesting limited influence on WA within this model. These findings highlight that farmers' willingness to adopt agricultural drone technology is largely

TABLE 7 Total effects on willingness to adopt (WA).

Predictor → WA	Total effect	95% CI (2.5, 97.5%)	Significance
ATT	0.799	[0.754, 0.838]	***
PE	0.139	[0.041, 0.243]	**
PU	0.127	[0.039, 0.215]	**
PP	0.135	[0.048, 0.218]	**
PEV	0.115	[0.032, 0.199]	*
PEI	0.097	[0.018, 0.170]	*
PSI	0.089	[−0.011, 0.184]	NS
PRC	0.064	[−0.176, 0.310]	NS
PEU	0.005	[−0.237, 0.247]	NS

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, NS, Not significant.

TABLE 8 Model fit.

Fit index	Value	Benchmark	Interpretation
GoF (Tenenhaus)	0.802	> 0.36	Very good model fit

shaped by their attitudes, which are, in turn, influenced by perceived promotional, functional, economic, and social factors.

The overall model fit was assessed using the Goodness-of-Fit (GoF) index which combines the performance of both the measurement and structural models (Table 8). The obtained GoF value of 0.802 exceeds the recommended threshold of 0.36, indicating a very good model fit (Sanchez, 2013). This suggests that the model provides a robust representation of the data and adequately captures the underlying relationships among the constructs, thereby supporting the validity and explanatory power of the proposed theoretical framework.

Discussion

This study sought to understand the psychological, social, and economic factors influencing farmers' adoption of drone technology as part of India's broader transition to Agriculture 4.0, with empirical data collected from Haryana and Uttar Pradesh, two agriculturally vital states in the Indo-Gangetic Plain. This region is not only characterized by intensive cropping systems but also represents India's high-potential zone for early technological adoption due to its relatively better infrastructure, access to extension services, and exposure to mechanized farming.

The measurement model showed strong reliability and validity, with Cronbach's alpha values above 0.97 and AVE values exceeding 0.91 for all constructs. These values indicate that the constructs such as Perceived Usefulness (PU), Perceived Ease of Use (PEU), Promotional Efforts (PE), and others were well-defined and consistently measured among the respondents. Factor loadings were consistently high (≥ 0.953), ensuring each item effectively represented its underlying latent construct. From the structural model, six out of eight proposed predictors had a significant influence on Attitude Toward Technology (ATT), namely Promotional Efforts, Perceived Usefulness, Peer Pressure, Perceived Economic Viability, Perceived Environmental Impact, and Perceived Social Impact. This confirms that both individual cognition and socio-environmental factors significantly influence

farmers' attitudes. In contrast, Perceived Ease of Use (PEU) and Perceived Risks and Challenges (PRC) were found to be statistically non-significant, suggesting a shift in mindset wherein modern farmers are becoming increasingly confident with new technologies, perhaps due to improved training, government-led demonstrations, or peer influence. As farmers become familiar with digital tools and mechanized systems, and with drones increasingly operated by service providers, the role of Perceived Ease of Use (PEU) diminishes in service-assisted adoption contexts. This may indicate a contextual shift in the TAM framework, where the relative importance of PEU diminishes in highly service-assisted or professionalized agricultural environments (Naspetti et al., 2017). Likewise, the influence of perceived risks may be diminishing due to improved awareness, institutional support, and positive peer experiences. This finding aligns with recent extensions of TAM and UTAUT, suggesting that risk perception may not directly influence attitude when the perceived value and performance benefits are strong (Almaiah et al., 2022).

The successful adoption of smart farming technologies, including drones, hinges on a complex interplay of awareness, infrastructure, peer learning, and perceived benefits. Drone technology, in particular, plays a crucial role in precision agriculture by enabling site-specific crop management, real-time monitoring of field conditions, pest and disease surveillance, and targeted application of inputs. In our study, the strong effects of PU, PEV, and PE suggest that functional utility and economic feasibility remain top priorities for farmers. This reinforces the idea that Agriculture 4.0 innovations must be positioned not only as "smart" or "sustainable" but also as pragmatic, profitable, and proven in real farm settings.

The high explanatory power of the model, $R^2 = 0.748$ for ATT and 0.639 for WA (Willingness to Adopt), demonstrates that the constructs collectively explain a substantial portion of farmers' technology adoption behavior. The critical path from ATT to WA ($\beta = 0.799$, $p < 0.001$) confirms that a positive attitude is the strongest single predictor of adoption intention, consistent with the Technology Acceptance Model (TAM) and related models applied

in agricultural innovation diffusion research (Dissanayake et al., 2022; Vasan and Yoganandan, 2024). Total effect analysis further supported the indirect influence of constructs like PU, PE, PP, PEV, and PEI on WA via ATT, revealing how external perceptions are channeled through attitudinal shifts. Notably, PEU, PSI, and PRC did not significantly influence WA, which may reflect a gap between farmers' awareness of social/environmental benefits or risks and their actual behavioral intentions. This highlights the need for more robust and localized extension education strategies that translate abstract sustainability concepts into tangible farm-level outcomes. The non-significant role of perceived risk (PRC) in this study diverges from several prior studies in risk-averse farming communities. However, in the relatively progressive farming belts of Haryana and western Uttar Pradesh, where drone demonstrations, digital literacy initiatives, and support services are more readily available, farmers appear less intimidated by the perceived risk. Government schemes such as the Sub-Mission on Agricultural Mechanization (SMAM) and the Digital Agriculture Mission (2021–2025) are likely playing a facilitative role, especially through subsidies, CHCs, and training (Press Information Bureau, 2022). Findings also reflect the changing role of peer influence (PP) in agricultural technology diffusion. They rely on peer experiences before making adoption decisions. This creates opportunities for social marketing and farmer-led promotion models, where visible early adopters can drive demand within their communities.

From a policy perspective, the strong impact of promotional efforts (PE) suggests that continued investment in awareness-building via Krishi Vigyan Kendras (KVKs), Farmer Producer Organizations (FPOs), and agri-tech startups is essential to scale adoption. The Indian government's recent push toward "Drone Didi" initiatives and the provisioning of drones to female SHGs also holds promise in making drone adoption more inclusive, particularly among marginalized and women farmers. Overall, the results strongly support the notion that technological adoption in agriculture is no longer hindered solely by access or affordability; rather, it is a function of perception, communication, and behavioral readiness. The implications for India's Agriculture 4.0 transformation are significant: by systematically addressing attitude formation through a mix of promotional, social, and economic interventions, India can accelerate adoption and ensure that smart technologies like drones reach scale, especially among the 86% of farmers who are small and marginal (World Economic Forum, 2021).

Implications of the study

The findings of this study have significant implications for policymakers, extension agencies, and agri-tech stakeholders aiming to promote drone adoption in Indian agriculture. The strong influence of farmers' attitudes on their willingness to adopt drone technology highlights the importance of targeted behavioral interventions. Promotional efforts, peer influence, and perceived economic viability emerged as critical drivers, suggesting that awareness campaigns, farmer-led demonstrations, and clear communication of economic benefits can substantially enhance adoption rates. The non-significance of perceived ease of use and risk suggests that once farmers are convinced of the utility and profitability of drones, technical concerns diminish. Therefore, strategies should prioritize early exposure,

trust-building, and value-based messaging over technical complexity, aligning closely with India's broader digital agriculture mission.

Limitations of the study

This study, while offering valuable insights into the adoption of agricultural drone technology, has several limitations. First, the research was geographically confined to Haryana and Uttar Pradesh, which may limit the generalizability of the findings to other regions with different agro-ecological, cultural, or infrastructural contexts. Second, the cross-sectional design restricts the ability to observe how attitudes and adoption intentions evolve over time, especially as exposure to drone technology increases. Third, the data relied on self-reported perceptions, which may be subject to social desirability bias and may not always reflect actual adoption behavior. Finally, the model primarily focused on psychological and social constructs, without incorporating policy, institutional, or infrastructural variables such as access to subsidies, availability of service providers, or regulatory frameworks that may also play a crucial role in adoption decisions. Future research should address these limitations through longitudinal, multi-regional, and multi-dimensional approaches.

Conclusion

This study provides robust empirical evidence on the determinants of agricultural drone adoption among farmers in Haryana and Uttar Pradesh, reinforcing the critical role of attitude shaped by promotional, functional, economic, and peer-related factors. The findings align with India's vision of Agriculture 4.0, where digital tools like drones are positioned as transformative solutions to enhance productivity and sustainability. The non-significant impact of ease of use and perceived risk indicates a growing maturity in farmer outlooks, where perceived benefits outweigh apprehensions. Policymakers, agri-tech firms, and extension agencies must focus on awareness-building, peer engagement, and value demonstration to accelerate adoption. As India moves toward a digitally empowered agricultural ecosystem, such behavioral insights will be essential to ensure inclusive and widespread technology diffusion.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving humans were approved by All methods used in this study were conducted in accordance with the relevant guidelines and regulations. The study received approval from the Research Ethics Committee of the Division of Agricultural Extension, ICAR-Indian Agricultural Research Institute, New Delhi, India. Informed consent was obtained from each participant, and their confidentiality was ensured throughout the study. The studies were conducted in accordance with the local legislation and institutional

requirements. The participants provided their written informed consent to participate in this study.

Author contributions

BB: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. RS: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. RP: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – review & editing. MN: Conceptualization, Formal analysis, Methodology, Supervision, Validation, Writing – review & editing. SQ: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – review & editing.

Funding

The author(s) declare that no financial support was received for the research and/or publication of this article.

Acknowledgments

The authors express their sincere gratitude to the Director and the Dean of ICAR-Indian Agricultural Research Institute, New Delhi, for providing constant support and necessary facilities for the successful completion of this work.

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Supplementary material

The Supplementary material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fsufs.2025.1169523/full#supplementary-material>

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