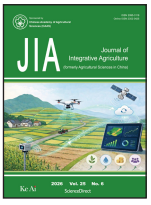
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RESEARCH ARTICLE

Drivers and barriers to unmanned aerial vehicle (UAV) adoption in agriculture: Evidence from Jiangxi Province, China

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Highlights

- We analyze factors affecting UAV adoption among Jiangxi (China) rice farmers using a structural equation model.
- Perceived usefulness and ease of use boost adoption intention, while perceived risk hinders it.
- Network externalities and peer influence also increase adoption likelihood, with perceived risk mediating this relationship.
- The findings offer valuable guidance for policymakers and industry stakeholders to encourage UAV use in agriculture.

Abstract

The adoption of plant-protection unmanned aerial vehicles (UAVs) in agriculture is gaining attention, yet empirical evidence on the factors affecting their uptake remains limited. This study investigates the factors influencing the adoption of UAVs among rice farmers in China's Jiangxi Province (n=260), utilizing a structural equation model grounded in the Technology Acceptance Model (TAM). Results indicate that perceived usefulness (β=1.274, P<0.001) and ease of use (β=0.146, P<0.001) have a positive influence on adoption intention, while perceived risk (β=–0.731, P<0.001) acts as a barrier. Network externalities also play a significant role, with peer influence amplifying the likelihood of adoption. Mediation analysis reveals that perceived risk mediates the relationship between network externalities and adoption (β=–0.569, P<0.05), underscoring the interplay between social factors and risk perception. Additionally, farm size (β=0.001, P<0.001) has a significant positive effect on adoption decisions, whereas education level, age, and planting experience show no significant impact. These findings provide critical insights for policymakers and industry stakeholders in designing targeted interventions, such as subsidies, training programs, and risk mitigation strategies, to promote the adoption of UAVs in agriculture.

Keywords: digital agriculture, unmanned aerial vehicles (UAVs), agricultural drones, Technology Acceptance Model (TAM)

1. Introduction

Digital agriculture aims to achieve higher-quality yields at a lower cost through the use of information and communication technologies (ICT). Digitalizing traditional agricultural practices is encouraged because it substitutes labor with capital (Heitkämper *et al.* 2023). This is particularly crucial for China, where the rural labor force is rapidly migrating to cities in search of better job opportunities (Gao *et al.* 2023). This significant decline in the agricultural labor force necessitates the adoption of digital technologies, which hold great potential to transform the agricultural sector by enhancing conventional farming methods. Digital transformation in farming incorporates various mobile remote sensing technologies, including satellites, aircraft, and UAVs, to support agricultural production. Among these technologies, unmanned aerial vehicles (UAVs) have significant potential in agriculture and are preferred over satellites and aircraft due to their flexibility of deployment, operational efficiency, and cost-effectiveness (Urbahs and Jonaite 2013; Kulbacki *et al.* 2018). The main applications of agricultural UAVs include aerial mapping, soil

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analysis, classification and scouting of crops, monitoring of drought, assessment of water stress, fertilizer application, livestock management, environmental monitoring, conservation of wildlife and forestry, and aerial pesticide spraying (Yinka-Banjo and Ajayi 2019; Avtar and Watanabe 2020; Radoglou-Grammatikis *et al.* 2020; Maddikunta *et al.* 2021; Rejeb *et al.* 2022).

Moreover, agricultural UAVs play a significant role in plant-protection by identifying crops' susceptibility to diseases, fungi, pests, and weeds. For this purpose, UAVs equipped with a combination of RGB, multispectral, hyperspectral, and thermal sensor systems can provide real-time, accurate crop health reports, ultimately assisting farmers in taking timely actions to control these threats to agriculture (King 2017; Zheng *et al.* 2020; Blasch *et al.* 2023). Using UAVs in agriculture enhances the efficiency of crop pest control, enabling farmers to streamline farm operations and reduce costs by minimizing labor, fuel, and pesticide/herbicide expenses. This disruptive technology can revolutionize digital agriculture by modifying farming practices, including planting, irrigation, field analysis, crop health monitoring, and crop spraying, to achieve enhanced operational efficiency. Moreover, its associated economic benefits are among the most vital factors in adoption (Papadopoulos *et al.* 2024).

Due to the potential benefits of UAVs for crop disease detection and aerial spraying, governments worldwide are developing various policies to accelerate the adoption of plant-protection UAVs (Beriya 2023; Nazarov *et al.* 2023; GOA 2022, p. 43). Similarly, the Chinese government has introduced various policies to promote the use of plant-protection UAVs in China's agriculture over the past decade (Appendix A).

1.1. Background

Over the years, these policies have been implemented in China at various scales and times (Appendix A). For example, in the 2014 "Comprehensively Deepening Rural Reform and Accelerating the Promotion of Agricultural Modernization" policy, the government emphasized strengthening agricultural aviation, providing technical training to farmers, and playing a leading role in modern agricultural demonstration areas (SCPRC 2014). The government began providing subsidies for purchasing agricultural UAVs in six key provinces in 2017, and this initiative was expanded nationwide by 2018. In one of the latest policies under the 14th Five-Year Plan, the government aims to promote using UAVs for agricultural protection services (Appendix A).

China produces and uses a large number of UAVs (SCIO 2024). The advancement of UAV technology and the growth of market potential have made agricultural UAVs a popular field. China's agricultural UAV market has become the world's largest industry, attracting many companies to invest in it. According to statistics from the Civil Aviation Administration of China, 832,000 UAVs were registered in the industry in 2021, including 160,000 agricultural UAVs, accounting for 19.2% of the total UAV registrations. The units increased from more than 4,000 in 2016 to 160,000 in 2021, and the operating area expanded from 6.67 million hectares in 2017 to 93.3 million hectares in 2021 (Hu *et al.* 2022). Overall, agricultural UAVs have garnered extensive attention from the government and society due to their advantages over manual operations in terms of operational efficiency (Parmaksiz and Cinar 2023), operational results (Quan *et al.* 2023), and environmental adaptability (Wachenheim *et al.* 2021).

Despite their potential benefits, government policy support, and the popularization of UAVs in China, the farming community has not adopted them at scale. Studies show that plantprotection UAVs in China have not been widely adopted nationwide, with their operating area accounting for less than 5% of the total cultivated land area, significantly lower than in developed countries (Chung and Scherer 2019). It is therefore crucial to identify the factors driving the adoption of UAVs in China's agriculture.

1.2. Literature review and research gap

A growing body of research has explored factors influencing technology adoption in agriculture, particularly using TAM and related frameworks. Studies have consistently found that perceived usefulness and ease of use are key determinants of technology adoption (Davis 1989; Venkatesh and Bala 2008). However, findings on external factors such as social influence, risk perception, and market structures remain inconsistent across studies. For example, some research suggests that network externalities play a crucial role in the diffusion of technology (Katz and Shapiro 1985; Kamal *et al.* 2020), while others argue that farmers rely more on individual experiences than on peer adoption (Marra *et al.* 2003). Similarly, perceived risk has been examined in agricultural technology adoption (Jayashankar *et al.* 2018; Liu and Liu 2024), yet its specific impact on UAV adoption remains underexplored.

Several previous studies have examined the factors influencing farmers' adoption of UAV technology. Zheng *et al.* (2019) identified technology awareness, gender, perceived usefulness, ease of use, and agricultural income ratio as key determinants. Degieter *et al.* (2023) highlighted both internal factors (age, gender, income, education, farm size, and perceived benefits) and external factors (cost, compatibility, and labor scarcity) affect the adoption of UAVs. Parmaksiz and Cinar (2023) found that government support is a positive driver. Quan *et al.* (2023) employed propensity score matching (PSM) to demonstrate that the adoption of UAVs increases revenue by reducing pesticide costs, frequency, and application time. Wachenheim *et al.* (2021) found that male gender, cultivated land area, village leadership, agricultural income percentage, access to borrowing options, and positive attitudes all enhance adoption intention in China.

While existing studies have examined technology adoption in agriculture using models such as the Technology Acceptance Model (TAM) and Diffusion of Innovations Theory, relatively few have focused specifically on UAV adoption. Despite these advancements, several research gaps persist. First, prior studies on UAV adoption primarily focus on economic feasibility and technical challenges, with limited attention to the social dynamics that shape farmers' adoption decisions. Second, while perceived risk and network externalities have been studied in other technological

contexts, their interaction in the adoption of UAVs remains unclear. Third, while perceived risk has been acknowledged as a barrier to the adoption of new agricultural technologies, its mediating role between network externalities and adoption intention has not been thoroughly examined.

Network externalities refer to the phenomenon where the value of a technology increases as more people adopt it. In the context of agricultural technology adoption, this implies that as more farmers adopt UAVs, the benefits extend beyond individual users to the broader farming community. These benefits can manifest in multiple ways, including greater access to shared resources such as UAV service providers, increased availability of technical support, and enhanced credibility of the technology, as its effectiveness is demonstrated through peer experience. Positive externalities can reduce uncertainty and risk perceptions among potential adopters, thereby increasing their likelihood of embracing the technology. Conversely, weak network externalities may hinder adoption if farmers perceive themselves as isolated users with limited external support or insufficient market penetration. This study examines the role of network externalities in the adoption of UAVs. It explores how perceived risk mediates the impact, shedding light on the social and economic dynamics influencing farmers' decisions to adopt technology.

This study advances the literature in three key ways: First, while previous studies have considered these factors individually, we integrate them into the TAM model to examine their combined effects on UAV adoption. This enables a more comprehensive understanding of adoption behavior in the agricultural sector. Second, unlike previous research that treats risk perception as a static barrier to adoption, we explore how it mediates the influence of network externalities. This distinction is crucial for understanding whether social influence can help alleviate risk concerns and thereby encourage adoption. Third, unlike general precision agriculture technologies, UAVs require a distinct investment in hardware, training, and compliance with regulations. Focusing on Jiangxi Province, a major rice-producing region with diverse agricultural conditions, this study provides empirical insights applicable to other regions where UAVs are being promoted for agricultural use. By isolating the adoption of UAVs from broader mechanization trends, this study provides targeted insights relevant to policymakers and industry stakeholders.

The study's practical contribution is that rice, China's second-largest grain crop, continues to suffer from outdated pest control methods despite advancements in sowing, transplanting, and harvesting techniques. With farmers averaging only 0.5 hectares of land (Wu *et al.* 2018), manual pest control is inefficient, prone to delays, wasteful of resources, and misses critical pest-control windows. Plant-protection UAVs conserve time, water, and pesticides, aligning with ecological and conservation priorities to support sustainable development. This study examines the factors influencing farmers' adoption of UAV technology, thereby promoting its use in rice farming and advancing agricultural modernization.

The rest of the article is structured as follows: Section 2 describes the methodology, providing an overview of the study area, data collection procedure, statistical data about the adoption of agricultural UAVs in China, details of the adapted TAM, description of selected variables, validity testing for the reliability of collected questionnaire data, and derivation of hypotheses. The results of the empirical analysis, including hypothesis testing, mediation analysis, and limitations are discussed in Section 3. The study's conclusions are presented in Section 4, along with policy recommendations and future perspectives.

2. Data and methods

2.1. Study area

To investigate farmers' willingness to adopt plant-protection UAVs, we analyzed the trend of UAV popularization in seven cities of Jiangxi Province, one of China's major rice-producing regions. Jiangxi is also among the first Chinese provinces to adopt agricultural UAVs (Chung and Scherer 2019) and was one of the six key provinces selected in the 2014 pilot project to provide subsidies for UAV purchases by the Chinese government.

Jiangxi, located in southeast-central China, south of the Yangtze River, is one of China's 13 major grain-producing regions and has consistently supplied commercial grain to national depots, playing a crucial role in ensuring food security (Zhao 2024). The Poyang Lake Plain and its surrounding regions are the primary grain-producing areas in Jiangxi. The Mufu and Jiuling Mountains border this area to the west, connecting to Poyang Lake and Lushan Mountain to the east. The terrain is mostly flat, with a dense network of rivers forming a lakeside plain. The climate is subtropical and humid, with an average annual temperature ranging from 16 to 20°C and a frost-free period of 246 to 284 days, creating ideal conditions for agriculture. This region is the largest grain production base in Jiangxi and one of China's most significant rice-growing areas, making it crucial for both national and regional food security (Zhao 2024).

Jiangxi Province is an ideal candidate for this study due to its significant role in rice production, one of China's primary staple crops, and its top priority in the country's food security policy. The region's agricultural practices are transitioning from traditional to modern, making it a pertinent location to study the adoption of new technologies, such as UAVs. Despite advancements in planting and harvesting, pest control methods remain outdated (JFPDSDPMO 2023), creating an opportunity to introduce plant-protection UAVs that could improve efficiency and align with ecological priorities. The small average landholding size of farmers in Jiangxi also highlights the potential benefits of UAVs, making it a relevant setting for this research.

The diverse topography and farming practices in Jiangxi further strengthen its suitability for this study. This diversity allows the survey to capture a comprehensive range of factors influencing UAV adoption, making the findings more generalizable across different farming environments. Moreover, Jiangxi's early adoption of UAVs, supported by government initiatives, positions it as a leading region in the technological advancement of agriculture. Other regions

and countries can use insights from this study to promote the adoption of UAVs in agriculture. Understanding factors like perceived usefulness, ease of use, network externalities, and risk perception can help design effective policies to enhance agricultural productivity and sustainability while addressing bottlenecks such as labor shortages.

2.2. Survey participant selection and sample size determination

For this study, we selected survey participants using a multi-stage stratified sampling approach, ensuring that farmers across various farm sizes, geographic locations, and technological exposure levels in Jiangxi Province are represented. Seven major rice-producing cities (Nanchang, Jiujiang, Pingxiang, Shangrao, Yichun, Yingtan, and Jingdezhen, primarily located in the northern part of the province) were initially identified based on agricultural census data and UAV adoption trends. Seven counties related to these cities were selected, followed by a random sampling of 21 villages within these counties. We conducted a power analysis to determine the optimal sample size, ensuring statistical robustness. The required sample size was calculated based on an expected effect size of f^2=0.15, a significance level of 0.05, and a power of 0.80, resulting in a minimum of 150 respondents. Ultimately, a total of 285 (12–15 per village) randomly selected farmers participated in the survey, ensuring adequate statistical power for hypothesis testing. We used data from 260 questionnaires for this study, discarding 25 responses due to omissions, overfilling, or incomplete information. The final sample comprised a mix of early UAV adopters, non-adopters, and potential future adopters, capturing diverse perspectives on the adoption of UAV technology.

The survey instrument was developed through expert consultations and pilot testing to refine the clarity and reliability of the questions. Data were collected through face-to-face and online interviews conducted by trained enumerators, ensuring consistency and reducing potential biases in self-reported responses. The online interviews were conducted for the farmers who were unavailable for face-to-face interviews during the survey visits.

The basic information of respondents shows that 95.14% of farmers have junior school or higher education, and a majority are in good health to perform daily agricultural operations in the rice field (Table 1). Around two-thirds of farmers are middle-aged (30–50 years), and about half (48.11%) have reasonably long experience in farming (6–20 years). It also shows the diversity of selected surveyed areas: 52% hilly areas, followed by plains (25%) and mountainous areas (19%). Large-scale rice-growing households, with a planting area of 500 mu or more, account for the largest proportion (34.6%). A mu is a Chinese land unit; 15 mu is equivalent to 1 hectare. Overall, these characteristics align with the general conditions prevailing in Jiangxi Province.

2.3. Description of agricultural UAV adoption in Jiangxi

The data on plant-protection UAVs in these areas show that large-scale farmers prefer UAVs for rice production over smallholders (Fig. 1). There is little difference between renting and purchasing UAVs for pest-control operations by large-scale farmers. However, small-scale farmers have relatively few purchasers of plant-protection UAVs due to the high costs of buying and maintaining them. Renting with maintenance services is a low-cost option that allows small-scale farmers to utilize both simultaneously, accounting for a significant

Table 1 Basic information of respondents

Item	Description	Frequency	Percentage (%)
Main work type	Farmer	187	71.89
	Migrant worker	15	5.95
	Self-employed	58	22.16
Age	Below 30 years	24	9.19
	30–40 years	83	31.89
	41–50 years	93	35.68
	51–60 years	56	21.62
	Over 60 years	4	1.62
Education level	Elementary school and below	13	4.86
	Junior school	83	31.89
	High school and technical high school	94	36.22
	College degree and above	70	27.03
Health status	Very good	188	72.43
	Good	69	26.49
	Not good	3	1.08
Land environment	Plain	63	24.23
	Lake district	7	2.70
	Mountainous area	49	18.85
	Hilly	136	52.30
	Basin	5	1.92
Rice planting experience	Less than 1 year	13	4.86
	1–5 years	73	28.11
	6–10 years	73	28.11
	11–20 years	52	20.00
	More than 20 years	49	18.92
Rice planting area	Below 50 mu[1)]	58	22.16
	50–200 mu	56	21.62
	200–500 mu	56	21.62
	500 mu and above	90	34.59

[1)] 1 ha=15 mu.

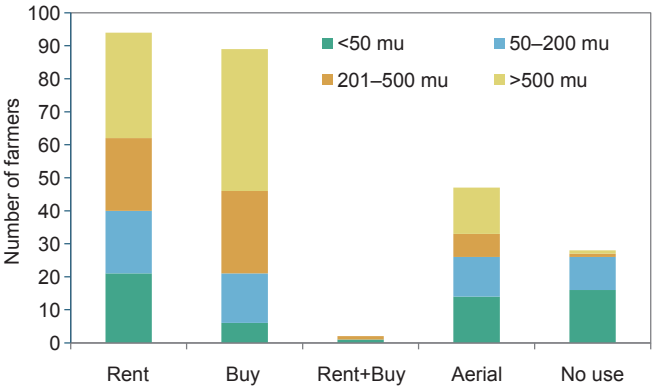


Fig. 1 Various uses of plant-protection unmanned aerial vehicles (UAVs). Each column shows the total number of farmers in each category. Each colored stack shows the share of different farm sizes in each category. mu is a Chinese land unit: 1 ha=15 mu.

proportion of the total. Aerial spraying is the third-largest service option for rice farmers, involving trained pilots from cooperatives or agri-companies using plant-protection UAVs to provide paid crop-protection services. These pilots are skilled in UAV operation, maintenance, spraying techniques, and safety protocols.

2.4. Theoretical foundation and measurement justification

The TAM has been widely used to analyze technology adoption, considering perceived usefulness and ease of use as key determinants (Davis 1989). Moreover, TAM has also been utilized in agricultural research to assess farmers' adoption trends of digital agriculture technologies, for example, precision agriculture (Adrian *et al.* 2005) and smart agriculture (Goel *et al.* 2021). However, the adoption of UAVs in agriculture involves additional psychological and contextual factors that influence decision-making. This study improves the model's explanatory power by integrating perceived risk and network externalities, drawing from established theories in innovation diffusion and consumer behavior.

In this study, perceived ease of use refers to farmers' belief that UAV technology is easily accessible. For this factor, we have selected three observable variables to analyze: the convenience of purchasing or renting a UAV, learning to use a plant-protection UAV for pesticide spraying, and accessing maintenance services in the region. These observable variables (and the ones described below) are measured using a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). If rice farmers believe that using plant-protection UAVs in rice production involves a complex process, they may consider adopting conventional crop protection practices. Therefore, a positive perception of rice farmers regarding the use of plant-protection UAVs is expected to positively impact the adoption rate of plant-protection UAVs (Table 2).

Perceived usefulness refers to a farmer's belief that UAV technology enhances crop production while reducing production costs. For this factor, four observable variables were selected: farmers' perception of using UAVs to reduce pesticide dosage, improvement in pesticide spraying efficiency, improvement in pest control effectiveness, and improvement in overall yield. The more positive the attitude towards the usefulness of plant-protection UAVs, the greater the willingness to adopt them. Other studies using the TAM in agricultural contexts have also employed similar definitions of "perceived ease of use" and "perceived usefulness," such as those of Flett *et al.* (2004), Scherer *et al.* (2019), Mohr and Kühl (2021) and Zarei *et al.* (2022).

Perceived risk has also been studied in the context of technology adoption, stemming from Perceived Risk Theory (Bauer 1960), which posits that individuals hesitate to adopt new technologies due to uncertainty and potential negative consequences associated with these technologies. For the adoption of UAVs, these risks may include concerns about high investment costs, operational safety, regulatory compliance, and technological failures (Featherman 2001; Featherman and Pavlou 2003). For this factor, we included four observable variables: inadequate subsidy, injury occurrence, high usage cost, and inability to adapt to new technologies (Table 2). Prior studies on agricultural technology adoption confirm that perceived risk negatively affects farmers' willingness to adopt new tools and automation (Marra *et al.* 2003; Li *et al.* 2020).

We incorporated network externalities based on the Network Externality Theory (Katz and Shapiro 1985), which posits that the perceived value of technology to consumers increases as more users adopt it. Regarding this factor, the primary observable variables used in this study are the adoption of plant-protection UAVs by small- and large-scale farmers and the total number of farmers who take the initiative to use agricultural UAVs (Table 2). Previous studies in agricultural technologies show that a farmer's adoption decisions are positively influenced if the farmer belongs to

Table 2 Description of selected variables

Latent variable	Code	Description
Perceived usefulness (X_1)	PU1	Using plant-protection UAVs (PP-UAVs) will reduce pesticide use.
	PU2	Using PP-UAVs will improve the efficiency of pesticide spraying.
	PU3	The effectiveness of PP-UAVs is better than that of manual labor.
	PU4	Using PP-UAVs for pesticide spray will increase crop production.
Perceived ease of use (X_2)	PEU1	PP-UAVs can be easily purchased or rented.
	PEU2	Whether it is easy to learn to operate PP-UAVs for spraying.
	PEU3	Whether it is possible to get PP-UAV services in the area.
Perceived risks (X_3)	PR1	Worry that government subsidies for PP-UAVs are insufficient.
	PR2	Worry about getting injuries from using PP-UAVs.
	PR3	Worry about the affordability of usage costs, such as maintenance and battery replacement.
	PR4	Worry about not being able to accept the changes brought by PP-UAVs.
Network externalities (X_4)	NE1	I feel more farmers around me are starting to take the initiative to learn about PP-UAV technology.
	NE2	I feel that more large-scale rice growers are using PP-UAVs.
	NE3	I feel that more small-scale rice growers use PP-UAVs.
Willingness to adopt (Y_1)	AC1	I plan to continue using of PP-UAVs.
	AC2	I will use PP-UAVs for rice production.
	AC3	I will recommend the use of PP-UAVs to farmers in my area.

social networks (e.g., cooperatives) (Yigezu *et al.* 2018). Awareness and adoption of UAVs for targeted agrochemical applications are driven by peer influence and informal knowledge-sharing networks (Kendall *et al.* 2022).

We adopted established definitions for perceived risk and network externalities to ensure consistency with prior research. Perceived risk is measured using indicators related to financial risk, performance uncertainty, and regulatory concerns, following the work of Featherman and Pavlou (2003) and Li *et al.* (2020). Network externalities are measured based on perceived peer adoption, availability of supporting services, and technological compatibility, adapted from Katz and Shapiro (1985) and Li K *et al.* (2023). After incorporating these theoretical perspectives, the adapted TAM used in this study provides a more comprehensive framework for understanding UAV adoption among farmers. These refinements enhance the model's ability to capture the psychological factors and external influences that shape adoption behavior.

2.5. Mathematical modeling of proposed adapted TAM

We employed the Structural Equation Model (SEM) to examine the causal relationship between the latent variables of the TAM. SEM is an econometric tool frequently used in the social sciences that includes two model types: the measurement model, a linear function of a set of observed variables, and the structural model, which defines the causal relationships among latent variables. In these models, latent variables are also referred to as unobserved variables. Observed variables are also referred to as manifest variables, indicator variables, or measured variables. Researchers can obtain the latter directly through observation or measurement, and the obtained data can be converted into quantitative data. The residual error term refers to the variability that external factors cannot explain but is due to internal factors, specifically random variability in the SEM.

The specific SEM model equations are given below:

$$\eta=\gamma\xi+\beta\eta+\varsigma \quad (1)$$

$$X=\lambda\xi+\delta \quad (2)$$

$$Y=\lambda\eta+\varepsilon \quad (3)$$

where λ, γ, and β are regression coefficients, ξ and η are vectors, and ς, δ, and ε are error terms. X denotes the vector of exogenous variables, and Y shows the vector of observed variables.

To elaborate on the mediating effect (Fig. 2-B), we have considered the model with an independent variable (X_1), a mediating variable (m), and a control variable (X_2) as an example,

$$y=a_1X_1+a_2X_2+\mu_1 \quad (4)$$

$$m=b_1X_1+b_2X_2+\mu_2 \quad (5)$$

$$y=a'_1X_1+a'_2X_2+b'm+\mu_3 \quad (6)$$

The coefficient a_1 in eq. (4) is the overall effect of the independent variable X_1 on the dependent variable y. In eq. (5), the coefficient b_1 is the effect of the independent variable X_1 on the mediating variable m. In eq. (6), b' is the effect of the intermediate variable on the dependent variable y after controlling for the effect of the independent variable X_1, and a'_1 is the direct effect of X_1 on the dependent variable y after controlling for the effect of the mediating variable m. Finally, μ_1–μ_3 are the error terms of the regression equations. In this relatively simple mediation model, the mediation effect is also the indirect effect, which is equal to the coefficient product b_1b', and its relationship with the total effect and direct effect is as follows:

$$a_1=b_1b'+a' \quad (7)$$

For the test of the coefficient product, i.e., the test of the mediation effect model, the mediation analysis method of SmartPLS 3.3.3 uses the Bootstrap method.

When the value of the indirect effect exceeds that of the direct effect, the mediation effect is considered significant; otherwise, it is not significant.

2.6. Data reliability and validity test

In this study, we considered several indicators, i.e., Factor Loading Correlation, Cronbach's Alpha value, Rho_A value, Combined Reliability (CR), and Average Extracted Variance (AVE), to test the reliability and validity of the selected variables. Results regarding these indicators were estimated using SmartPLS 3.3.3. We found that the Factor Loading Correlation value for each observed variable is higher than 0.6 (Table 3), Cronbach's Alpha value and Rho_A value are both

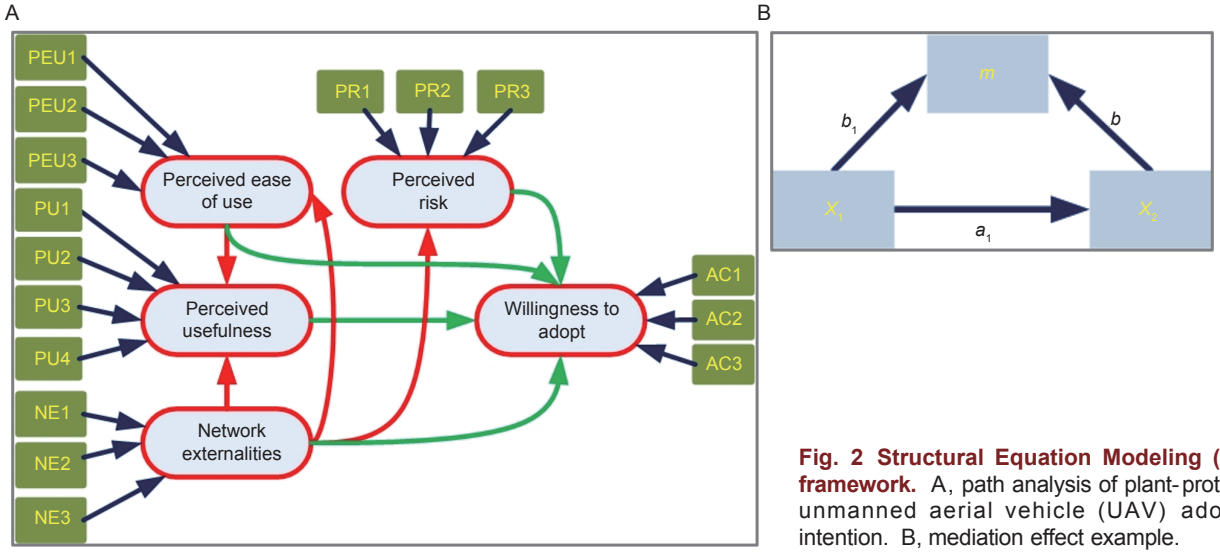


Fig. 2 Structural Equation Modeling (SEM) framework. A, path analysis of plant-protection unmanned aerial vehicle (UAV) adoption intention. B, mediation effect example.

Table 3 Reliability and validity test

Latent variable	Code	Mean	St. deviation	Factor loading	Cronbach's alpha	Rho_A	Combined reliability	Average extracted variation
X_1	PU1	1.6	0.491	0.868	0.819	0.875	0.897	0.686
	PU2	1.31	0.623	0.809				
	PU3	1.43	0.665	0.838				
	PU4	1.69	0.673	0.796				
X_2	PEU1	1.83	1.129	0.884	0.874	0.877	0.854	0.662
	PEU2	1.9	1.059	0.870				
	PEU3	1.93	1.118	0.927				
X_3	PR1	1.95	0.988	0.683	0.783	0.895	0.861	0.610
	PR2	1.48	0.767	0.737				
	PR3	2.28	1.051	0.829				
	PR4	1.58	0.594	0.863				
X_4	NE1	1.75	0.775	0.798	0.724	0.851	0.842	0.641
	NE2	1.71	0.854	0.882				
	NE3	3.11	1.434	0.714				
Y_1	AC1	1.55	0.598	0.909	0.713	0.742	0.865	0.638
	AC2	1.54	0.676	0.924				
	AC3	2.12	0.847	0.620				

greater than 0.7, CR is greater than 0.8, and the AVE value is greater than 0.6. These values indicate that the collected survey data have high reliability and validity. Moreover, the greater square root AVE values (shown in Table 4) for latent variables indicate that the scale has good discriminant validity.

We propose the following hypotheses to test the relationships:

H1: Perceived usefulness positively promotes the willingness to adopt plant-protection UAVs.

H2: Perceived ease of use positively promotes the willingness to adopt plant-protection UAVs.

H2a: Perceived ease of use positively contributes to perceived usefulness.

H3: Risk perception hinders willingness to adopt plant-protection UAVs.

H4: Network externalities improve the adoption of plant-protection UAVs.

H4a: Network externalities positively contribute to perceived usefulness.

H4b: Network externalities positively promote the perceived ease of use.

H4c: Network externalities negatively contribute to perceived risk.

To isolate other factors influencing the adoption of plant-protection UAVs, we used the respondents' educational level, age, physical health, planting experience, and planting scale as additional independent variables. For this analysis, we used SPSS 27 to run a binary logit regression analysis.

3. Results and discussion

3.1. Hypothesis testing

This section presents the empirical validation of the hypotheses based on the results of SEM. Our results reveal significant insights into the factors influencing farmers' adoption of plant-protection UAVs, offering confirmation and extension of existing research findings (Table 5, Fig. 3). The results confirm that perceived usefulness (H1) has a significant influence on UAV adoption, suggesting that farmers are more likely to adopt UAVs when they recognize tangible benefits, such as improved efficiency and cost savings. Similarly, ease of use (H2) positively affects adoption, supporting the idea that intuitive and accessible UAV technology encourages its adoption among farmers.

On the other hand, perceived risk (H3) negatively impacts adoption, highlighting farmers' concerns about technical failures, investment risks, and regulatory uncertainties. The concept of perceived risk in UAV adoption encompasses multiple dimensions, including farmers' concerns that may hinder their willingness to use plant-protection UAVs. These risks include financial uncertainties, such as insufficient government subsidies, and high operating costs, including maintenance and battery replacement. Additionally, farmers worry about potential safety hazards and whether they can adapt to the technological changes introduced by UAVs. Field observations indicate that economic risk is the most influential factor, as farmers are highly sensitive to cost-related concerns when evaluating new agricultural technologies. Fig. 1 also illustrates that small-scale farmers, who are typically financially weak, constitute the largest share of the 'non-users' category of farmers in this study. The findings suggest that targeted policy interventions, such as subsidies, insurance programs, and technical training, could help mitigate these perceived risks and encourage wider UAV adoption.

According to the path hypothesis H4, as demonstrated by the results of H4a and H4b, network externalities have

Table 4 Average variance extracted (AVE) square root value of latent variables and variable correlation coefficient

Latent variable	X_1	X_2	X_3	X_4	Y_1
X_1	0.829				
X_2	0.678	0.794			
X_3	–0.622	–0.656	0.749		
X_4	0.608	0.527	–0.704	0.768	
Y_1	0.584	0.503	–0.623	0.679	0.756

Table 5 Significance analysis of influence path

Hypothesis	Path	Coefficient	*T*-value	*P*-value	Significance	Test results
H1	$X_1 \rightarrow Y_1$	1.274	14.101	***	Significant	Established
H2a	$X_2 \rightarrow X_1$	0.835	29.255	***	Significant	Established
H2	$X_2 \rightarrow Y_1$	0.146	5.565	***	Significant	Established
H3	$X_3 \rightarrow Y_1$	–0.731	–12.400	***	Significant	Established
H4a	$X_4 \rightarrow X_1$	0.103	1.785	0.079	Not significant	Not established
H4b	$X_4 \rightarrow X_2$	0.027	2.935	0.122	Not significant	Not established
H4c	$X_4 \rightarrow X_3$	–0.238	–2.519	***	Significant	Established
H4	$X_4 \rightarrow Y_1$	0.220	2.934	***	Significant	Established

***, significant at 1% level.

no significant impact on perceived usefulness or ease of use. One possible explanation is that while social influence and peer adoption can play some role in encouraging UAV adoption, they do not necessarily change an individual farmer's intrinsic perception of how useful or easy to use the technology is. Farmers may evaluate UAVs based on personal experience, training, or technical demonstrations rather than relying solely on peer adoption. For example, prior studies on agricultural technology adoption (e.g., Maertens *et al.* 2020) have shown that farmers actively participating in hands-on local farming activities, such as farmer-managed demonstration plots, are more likely to incorporate multiple aspects of new technologies into their practices.

Additionally, UAV operation involves a learning curve, and even if many farmers in a community adopt the technology, new users may still perceive it as complex unless they receive direct training or experience. A combination of questionnaire responses and field observations also suggests that perceived usefulness is often shaped by economic considerations such as cost savings and yield improvements rather than by network effects. The absence of a significant link between network externalities and ease of use further supports this idea, indicating that peer influence alone is insufficient to reduce perceived complexity without complementary education and training initiatives. These findings underscore the need for targeted interventions that promote the adoption of UAVs through peer networks and enhance farmers' understanding of UAV benefits and usability through structured training programs.

The result of H4c shows that network externalities have a significant negative effect on perceived risk. The demonstration effect of more farmers using UAVs in the surrounding area, along with their suggestions and outcomes after using this technology, provides them with a sense of the potential risks this new technology could pose, helping non-users gauge the potential changes it could bring. The more farmers in the vicinity use UAVs for rice production, the lower the perceived risk for the non-users.

The finding that network externalities influence perceived risk but not perceived usefulness or ease of use highlights an interesting asymmetry in the diffusion of UAV technology. From a broader technology diffusion perspective, this suggests that social influence plays a stronger role in reducing uncertainty and alleviating fears rather than in shaping initial perceptions of usefulness or usability. In contrast to consumer technologies, where peer adoption might directly enhance perceived usefulness (e.g., smartphones or social media platforms), agricultural innovations often require individual assessment through experience and demonstration before their benefits become apparent. This outcome aligns with Rogers' (2003) Diffusion of Innovations theory, which emphasizes that observability and trialability are critical for adoption in agricultural contexts.

Moreover, this asymmetry suggests that while social networks effectively validate concerns about safety and reliability, they are less influential in altering fundamental perceptions of the benefits or user-friendliness of UAVs. This finding aligns with previous studies on precision agriculture technologies (e.g., Garbach and Morgan 2017), which found that while peer networks reduce uncertainty about risks, personal experience plays a greater role in improving perceived usefulness and ease of use. Consequently, policymakers and technology promoters should recognize that peer influence alone is insufficient to drive adoption and should complement social diffusion strategies with structured training programs, field demonstrations, and financial incentives to enhance the perceived benefits and usability of UAVs.

Our results are comparable to those in the existing literature on technology adoption in agriculture. Perceived usefulness and ease of use, consistent with Davis (1989) and

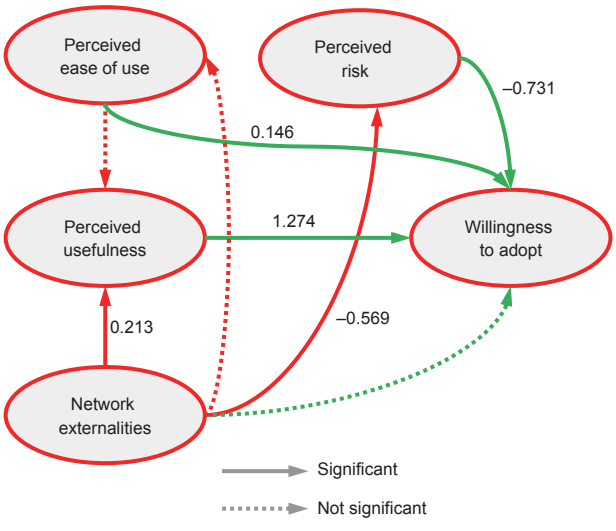


Fig. 3 Path diagram for unmanned aerial vehicle (UAV) adoption. The numbers shown in the figure are path coefficients.

related TAM-based studies, reinforce that utility and usability are key drivers of adoption. However, our study further highlights their interaction with socio-economic factors. The findings on the importance of perceived usefulness and ease of use align with the conclusions of Wachenheim *et al.* (2021), who demonstrate that perceived usefulness has a positive impact on the adoption of UAVs among farmers. Han *et al.* (2022) found that perceived ease of use and usefulness have a positive effect on the adoption of UAVs for pesticide application among farmers in China's Shaanxi Province. However, our study extends these findings by highlighting that network externalities, while influencing perceived risks, do not significantly impact perceived usefulness or ease of use. Li J *et al.* (2023) demonstrated that among cotton farmers in China, perceived usefulness has a positive effect, whereas technology risk negatively affects adoption intentions for smart agricultural technology.

The findings provide actionable insights for stakeholders in agricultural technology promotion and policymaking. Since perceived usefulness and ease of use are strong determinants of adoption, extension services should focus on providing practical demonstrations and training programs to familiarize farmers with the use of UAVs. Given the negative impact of perceived risk, policies should address key concerns through subsidies, technical support, and insurance schemes for users of UAVs. The significant role of network externalities suggests that policymakers and industry stakeholders should promote early adopters as influencers, leveraging farmer cooperatives and social networks to encourage diffusion. In terms of methodological advancements, our study employed mediation analysis to dissect the pathways through which network externalities influence adoption intention, offering a more detailed exploration than the logistic regression models used in other studies. Future research should incorporate qualitative approaches, such as in-depth interviews or case studies, to complement survey findings and provide richer insights into how perceived risk and network externalities influence adoption decisions.

3.2. Mediation analysis

We conducted a mediation analysis to examine the role of perceived usefulness, perceived ease of use, and perceived risk as mediating variables between network externalities and adoption intention. Additionally, we assessed perceived usefulness as a mediator between perceived ease of use and adoption intention (Table 6, Fig. 3).

The results indicate that neither perceived usefulness nor perceived ease of use mediate the effect of network externalities on adoption intention for UAVs. This suggests that simply observing more farmers using UAVs nearby does not necessarily lead an individual farmer to perceive UAVs as more useful or easier to operate. Unlike technologies with strong social influence, where widespread adoption signals increased reliability or practicality, the adoption of UAVs in agriculture may depend more on firsthand experience than indirect observations. Farmers may require direct exposure, such as personal trials or peer demonstrations, to evaluate the benefits and usability of UAVs rather than relying on the number of adopters in their vicinity. This finding aligns with Tucker (2017), who noted that network externalities may have a limited impact on technology adoption when decision-making is driven by individual experiences rather than broader network influences.

However, perceived risk plays a significant mediating role. As more farmers adopt UAVs, the perceived risk decreases, resulting in increased acceptance of the technology. This outcome is consistent with Hong and Kim (2002), who found that reduced perceived risk, facilitated through network demonstrations, has a positive impact on the adoption of agricultural technology.

Furthermore, we identified a partial mediating effect of perceived usefulness in the relationship between perceived ease of use and the intention to adopt. This suggests that improvements in ease of use and affordability enhance perceived usefulness, which in turn encourages the adoption of UAVs by rice farmers. This finding aligns with Kim and Garrison (2009), who demonstrated that perceived ease of use significantly influences perceived usefulness and subsequent adoption of new technologies.

In summary, while network externalities influence adoption intention by reducing perceived risk, individual experiences and ease of use remain critical factors. These insights deepen the understanding of technology adoption in agriculture, complementing prior research.

3.3. Other factors affecting the adoption of plant-protection UAVs

Our analysis indicates that factors such as farmers' education level, age, physical health, and planting experience do not significantly influence their adoption of plant-protection UAVs (Table 7). However, farm size plays a crucial role, with larger-scale rice farmers more likely to adopt UAV technology for crop protection. This preference stems from the higher efficiency and reduced labor demands of UAV-based pesticide application compared to manual methods, which require more time and investment in labor. These findings align with those of Michels *et al.* (2020), who reported that larger farms are more likely to adopt precision agriculture technologies, including UAVs, due to their potential to reduce costs and improve operational efficiency. Similarly, Pathak *et al.* (2019)

Table 6 Mediating effect analysis

Path	Direct effect	Indirect effect	Conclusion
Network externalities→Perceived usefulness→Willingness to adopt	0.554	0.539	The mediating effect is not significant
Network externalities→Perceived ease of use→Willingness to adopt	0.554	0.416	The mediating effect is not significant
Network externality→Perceived risk→Willingness to adopt	0.554	–0.569*	The mediating effect is significant
Perceived ease of use→Perceived usefulness→Adoption intention	0.182	0.213*	The mediating effect is significant

*, significant at 10% level.

Table 7 Regression analysis of the use of plant-protection unmanned aerial vehicles (UAVs)

Variable	*β*	Standard error	Wald	Degree of freedom	Significance	Exp (*β*)
Education level	0.565	0.363	2.428	1	0.119	1.759
Age	0.152	0.364	0.174	1	0.677	1.164
Health status	–0.046	0.563	0.007	1	0.934	0.955
Planting experience	–0.466	0.307	2.297	1	0.130	0.628
Planting scale	0.009	0.003	10.865	1	0.001***	1.009
Constant	0.163	1.752	0.009	1	0.926	1.177

emphasized farm size as a key factor in technology adoption, as larger farms often have greater financial capacity to invest in modern agricultural innovations.

In addition, we evaluated the difficulty of hiring workers for plant-protection tasks and found that 72% of farmers find it moderately or significantly difficult to hire labor for these tasks. This challenge further drives the preference for machinery over manual labor among farmers with large-scale operations, as observed by Michels *et al.* (2020) and corroborated by Koundouri *et al.* (2006), who noted that labor shortages and high labor costs are significant factors pushing farmers towards mechanization and technological adoption in agriculture. These insights are consistent with the findings from studies by Zhang *et al.* (2019) and Ma *et al.* (2018), which found that larger households tend to reduce their use of agricultural machinery due to a sufficient labor supply. This convergence of evidence across different regions and types of agricultural practices underscores the broader applicability of these findings, suggesting that similar patterns may be observed in other agricultural contexts.

Overall, these results underscore the significance of farm size and labor availability in the adoption of plant-protection UAVs, underscoring the need for policies and support mechanisms that address these critical factors to promote the broader adoption of agricultural technologies.

3.4. Economic and practical interpretations of results

The findings in this study reveal several key insights from both economic and practical perspectives. The significant impact of perceived usefulness on UAV adoption suggests that farmers are motivated by the potential cost savings and efficiency gains associated with UAV technology. From an economic standpoint, UAVs reduce pesticide use and optimize labor productivity, resulting in direct cost savings. However, the capital investment required to purchase and operate UAVs can be a critical barrier for many smallholder farmers. This capital requirement highlights the need for financial support mechanisms such as government subsidies and cooperative ownership models.

Similarly, the positive relationship between ease of use and adoption suggests that farmers are more likely to embrace UAVs when they perceive them as easier to operate. Practical adoption challenges arise when farmers lack the necessary technical knowledge or access to relevant training programs. Farmers may not fully adopt a user-friendly UAV system without adequate training. Therefore, developing structured UAV training programs is crucial to ensure farmers can effectively integrate UAV technology into their farming operations.

The role of perceived risk as a deterrent to adoption aligns with economic theories of risk aversion in investment decisions. Farmers, particularly small-scale ones with limited financial resources, often hesitate to adopt new technologies due to concerns about economic risks (e.g., uncertainty about returns on investment), operational risks (e.g., UAV failures or technical malfunctions), and regulatory risks (e.g., evolving policies on the use of UAVs). These risks discourage adoption despite the potential benefits. To mitigate these concerns, policymakers should consider introducing insurance schemes for UAV-related failures and simplifying regulatory frameworks to provide clearer guidelines for farmers.

The influence of network externalities on adoption, but not on perceived usefulness or ease of use, is particularly noteworthy. This suggests that seeing peers adopt UAVs increases farmers' confidence in the technology, but it does not necessarily change their perception of its usefulness or ease of use. In economic terms, this reflects herd behavior in technology adoption, where social influence reduces perceived uncertainty but does not substitute for firsthand experience. This finding suggests that while peer demonstrations and farmer cooperatives can increase adoption rates, they must be supplemented by direct financial incentives and training programs to enhance farmers' confidence in UAV technology.

3.5. Limitations

While this study offers valuable insights into the factors influencing the adoption of UAVs, several limitations must be acknowledged. First, the research is based on data collected from Jiangxi Province, which, although diverse in agricultural practices, may not fully represent the broader Chinese agricultural landscape. Future research should broaden its geographical scope to include multiple provinces, thereby enhancing the generalizability of the findings. Second, this study may be subject to self-selection bias, as respondents with internet access could be overrepresented. Future research should tackle these limitations by ensuring a more balanced sample and accounting for regional differences. Lastly, while this study examines UAV adoption using an extended TAM framework, additional behavioral and economic factors - such as farmers' risk tolerance, government policy changes, and considerations for environmental sustainability - should be explored in future research to develop a more comprehensive understanding of UAV adoption in agriculture.

4. Conclusion and policy recommendations

This study employs SEM based on an adapted TAM to

investigate the factors influencing the adoption of plant-protection UAVs among rice farmers in China. Our findings indicate that perceived usefulness, encompassing improved operational efficiency, environmentally friendly pesticide application, and enhanced production, positively influences adoption. Similarly, perceived ease of use, encompassing ease of learning and accessibility, also encourages adoption. Moreover, perceived usefulness mediates the relationship between perceived ease of use and adoption intention, reinforcing farmers' recognition of the advantages of UAVs over manual crop protection methods.

Conversely, perceived risk negatively impacts adoption and significantly mediates the relationship between network externalities and the intention to adopt. Farmers become hesitant when they hear about the problems others face using UAVs. While network externalities significantly influence perceived risk, they do not directly impact perceived usefulness, perceived ease of use, or willingness to adopt. This suggests that the number of farmers using UAVs primarily influences how others perceive the risks rather than directly shaping their assessment of the technology's benefits or ease of use.

Based on our empirical findings, we propose several policy measures to accelerate the large-scale adoption of plant-protection UAVs in China. First, demonstration programs should be expanded, leveraging the experiences of early adopters to reduce perceived risks and build confidence among farmers. Large-scale promotion meetings, on-site professional training, and guidance sessions should be organized to enhance practical knowledge and facilitate hands-on learning. Second, media outreach should be strengthened through targeted campaigns across social media, radio, and TV, to improve awareness and understanding of the benefits of UAVs, such as efficiency, ease of use, and environmental advantages. Third, financial and service support should be optimized. The government should introduce subsidies and cost-sharing mechanisms to reduce purchase and maintenance costs, particularly for small- and medium-scale farmers. Service teams should be deployed to provide technical assistance and alleviate concerns about operational challenges. Fourth, UAV cooperatives should be promoted to enable shared ownership and cost reduction, modeled after existing shared mechanization services used in China. Fifth, the authorities should strive to simplify the registration of UAVs, pesticide application standards, and operator certification. By implementing these targeted strategies, policymakers can enhance the adoption of UAVs among small-scale farmers, ensuring that the technology delivers tangible benefits while addressing economic, technical, and informational barriers.

While this study focuses on Jiangxi Province, the findings have broader implications for the adoption of UAVs in agriculture in China and globally. Many agricultural regions worldwide, particularly in developing economies, face similar challenges regarding labor shortages, farm-size constraints, and the need for technological interventions to enhance productivity. Countries with extensive rice farming systems, like India, Pakistan, Thailand, and Vietnam, could benefit from UAV technology recommendations under similar adoption dynamics. Additionally, UAVs hold potential for other high-value crops, such as fruits, vegetables, and specialty grains, where precision spraying and monitoring can significantly reduce input use and environmental impact. Policy recommendations should extend beyond China to address global concerns related to the adoption of UAVs. Governments and industry stakeholders should implement targeted subsidy programs, provide technical training, and create regulatory frameworks that ensure safe and effective UAV operations. Moreover, international collaborations and knowledge exchange platforms can facilitate the transfer of best practices across countries, thereby accelerating the adoption of UAVs in the agricultural sector. Lastly, future research should investigate cross-country comparative studies to better understand how regulatory environments, infrastructure, and socio-economic factors impact global UAV adoption.

Declaration of competing interest

The authors declare that they have no conflict of interest.

Declaration of generative AI and AI-assisted technologies in the writing process

The authors declare that they did not use AI in the preparation and writing of this manuscript.

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