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A Study on the Acceptance Willingness and Driving Factors of Agricultural Drones Among Smallholder Farmers in Liaoning Province

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Abstract : This study investigates the acceptance willingness and driving factors of agricultural drones among 229 smallholder farmers in Liaoning Province. Based on the UTAUT model and incorporating policy support variables, the research explores their attitudes toward adopting agricultural drones.A stratified random sampling method was employed to select smallholder farmers from six regions within the province for in-person interviews and online questionnaires. SPSS 27.0 was used for reliability and validity testing, correlation analysis, and multiple regression analysis.Results indicate that the questionnaire demonstrated good reliability and validity. Performance perception, perceived ease of use, social environment, and policy support all exerted significant positive effects on smallholder farmers' acceptance intention, with performance perception having the strongest influence and perceived ease of use the weakest. Based on empirical findings, the study proposes countermeasures including strengthening benefit guidance, establishing a socialized promotion network, optimizing the policy support system, and improving drone service models. These measures aim to enhance smallholder farmers' acceptance of agricultural drones and promote the intelligent transformation of agriculture.

Keywords: Smallholder farmers; Agricultural drones; Acceptance willingness; Driving factors

1 Introduction

Against the backdrop of accelerating global agricultural digitalisation, agricultural drones have emerged as pivotal equipment in modernising farming. Leveraging their efficiency, precision and cost-saving advantages, they have become a key solution to overcoming traditional agricultural production bottlenecks. As a major agricultural nation, China has persistently advanced agricultural technological progress in recent years. The application of agricultural drones in plant protection, seeding, and monitoring has expanded significantly, with accelerating technological iteration. However, the focus of promotion has predominantly centred on large-scale farming entities, while research and practical implementation tailored to smallholder farmers—who constitute the absolute majority of agricultural producers—remain relatively underdeveloped[1].

Liaoning Province, a major grain-producing region in China, cultivates staple crops such as maize and rice across over 70% of its arable land, with agriculture playing a pivotal role in its regional economy. According to data from Liaoning's Third National Agricultural Census, the province has 5.527 million agricultural households, of which only 127,000 are large-scale operations. Smallholder farmers constitute over 97% of the total, remaining the core force in agricultural production. However, accelerated urbanisation has led to a significant outflow of young and able-bodied rural labour, exacerbating Liaoning's agricultural labour shortage.Concurrently, labour costs have risen steadily, with average daily wages for agricultural workers increasing by over 8% annually over the past five years. This poses severe challenges to the traditional production models of smallholder farmers. Agricultural drones can cover 80-120 mu (approximately 5.3-8 hectares) per day for crop protection operations – 15-20 times the efficiency of manual labour – while reducing pesticide wastage by 15-20%. Their advantages of precision application, high operational efficiency, and cost-saving benefits align precisely with the core needs of smallholder farmers[2] .

Currently, Liaoning Province has launched pilot programmes for agricultural drone adoption in Dalian, Tieling and other regions, facilitating technology implementation through skills training and policy subsidies. Dalian City plans to add 355 agricultural drones by 2025, expanding operational scenarios from crop protection spraying to seed sowing, crop monitoring and other domains[3] .However, research indicates that smallholder farmers' acceptance of agricultural drones remains relatively low. Common issues include insufficient awareness, weak policy perception, and limited service accessibility, which constrain the technology's widespread adoption. Therefore, systematically investigating smallholder farmers' willingness to adopt agricultural drones and the core drivers in Liaoning Province not only provides practical pathways to address their production challenges but also holds significant practical implications for accelerating regional agricultural digitalisation and safeguarding national food security.

Theoretically, existing studies on agricultural UAV acceptance predominantly rely on the generic UTAUT model, lacking targeted consideration of regional characteristics such as the ageing, part-time nature, and small-scale operations typical of smallholder farmers. Furthermore, integrated research on policy support—a critical external variable—remains insufficient. Building upon the UTAUT framework, this study incorporates policy support variables tailored to the characteristics of Liaoning Province's smallholder farmers, thereby optimising the theoretical framework. This research fills a regional gap in studies examining agricultural technology adoption among smallholders in major grain-producing areas, enriches empirical findings on UAV acceptance, and provides theoretical references and methodological insights for similar regional investigations.

At the practical level, identifying key factors influencing smallholder adoption intent provides precise data support for governments to formulate differentiated promotion policies and for enterprises to optimise product and service offerings. Targeted measures to lower the cost, cognitive, and service barriers to technology adoption among smallholders can drive the scaled application of agricultural drones in rural Liaoning. This, in turn, enhances agricultural productivity, reduces environmental pressures, and contributes to green sustainable agriculture and rural industrial revitalisation.

Accordingly, this study first defines core concepts such as smallholder farmers and agricultural drones, systematically reviews the application of the UTAUT model, agricultural technology diffusion, and existing research on agricultural drone promotion both domestically and internationally, thereby identifying gaps in current scholarship[4]. Secondly, a driver model is constructed comprising four core independent variables—performance cognition, operational perception, social environment, and policy support—with farmer individual characteristics as control variables and adoption intention as the dependent variable. A survey questionnaire tailored to smallholder cognitive levels is designed. Subsequently, employing stratified random sampling, six regions in Liaoning Province—Shenyang, Dalian, Tieling, Jinzhou, Yingkou, and Dandong—were selected. These areas encompass diverse terrains including plains and hills, and encompass both maize and rice production zones. Primary data from 229 smallholder farming households was collected through a combination of face-to-face interviews and online questionnaires. Finally, SPSS 27.0 was employed to conduct reliability and validity testing, correlation analysis, and multiple regression analysis. This validated the influence of each variable on adoption willingness, ultimately proposing targeted and actionable policy recommendations. These findings provide robust support for advancing the adoption of agricultural drones among smallholder farmers and facilitating the intelligent transformation of agriculture.

2 Research Design

2.1 Variable Definition and Research Hypotheses

Based on the operational characteristics of smallholder farmers in Liaoning Province and existing research findings, the following variables were selected: Performance Perception, Perceived Ease of Use, Social Environment, and Policy Support as core independent variables; Farmer Individual Characteristics as control variables; and Acceptance Intention as the dependent variable. SPSS analysis was used to verify the influence of each variable on acceptance intention, leading to the following research hypotheses:

H1: Performance perception has a significant positive effect on smallholder farmers' willingness to adopt agricultural drones;

H2: Perceived ease of operation significantly and positively influences smallholder farmers' willingness to adopt agricultural drones;

H3: Social environment has a significant positive effect on smallholder farmers' willingness to adopt agricultural drones;

H4: Policy support has a significant positive effect on smallholder farmers' willingness to adopt agricultural drones.

Variable Definitions: (1) Performance Perception: Smallholder farmers' actual recognition of drones' ability to enhance operational efficiency, reduce production costs, and increase crop yields; (2) Perceived Operation: Smallholder farmers' subjective assessment of drone operational difficulty and learning costs; (3) Social Environment: Influence from external groups such as relatives, neighbors, agricultural cooperatives, and village officials through demonstration and recommendation;(4) Policy Support: Perceived level of government support policies such as purchase subsidies, operational training, and technical services; (5) Adoption Intent: Smallholder farmers' willingness to use, lease, or purchase agricultural drones in the future; (1) Control Variables: Individual farmer characteristics including gender, age, education level, farm size, and part-time farming status.

2.2 Questionnaire Design

The questionnaire comprises three sections: Section One covers individual farmer characteristics, including gender, age, education level, farm size, and secondary occupation status; Section Two presents the core variable scales using a 7-point Likert scale (1=Strongly Disagree, 7=Strongly Agree), consisting of 20 items: 4 on performance expectations, 4 on effort expectations, 4 on social influence, 4 on policy support, and 4 on acceptance willingness;The third part consists of open-ended questions to gather farmers' suggestions and concerns regarding drones.

2.3 Sample Selection and Data Collection

A stratified random sampling method was employed, selecting six regions in Liaoning Province: Shenyang, Dalian, Tieling, Jinzhou, Yingkou, and Dandong. These areas encompass diverse terrains including plains and hills, and include both corn and rice-producing regions.The survey was conducted from October to December 2025. A total of 230 questionnaires were distributed through a combination of in-person interviews and online surveys, with 229 valid responses collected, yielding a valid response rate of 99.6%. Sample characteristics are as follows:

(1)Gender Distribution

The gender distribution of the survey sample shows 106 female respondents (46.29%) and 123 male participants (53.71%). As illustrated in Figure 1, the gender composition exhibits a slightly higher proportion of male respondents.

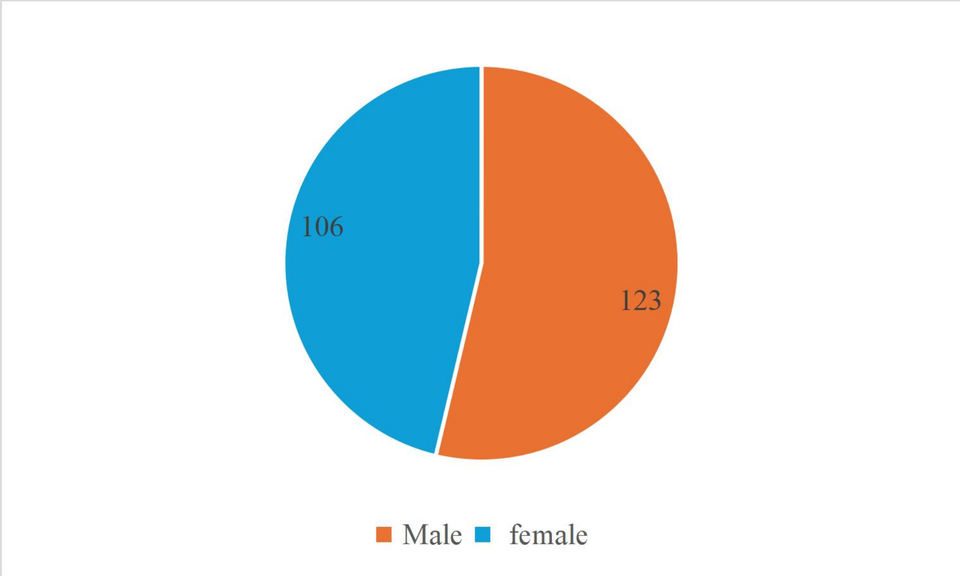

Figure1 Gender Distribution of Survey Participants

(2)Age Distribution

The age structure is dominated by middle-aged and young adults, with the 36-54 age group accounting for the highest proportion at 48.03% (110 cases). This is followed by those aged 35 and under at 27.51% (63 cases) and those aged 55 and over at 24.45%(56 cases). As shown in Figure Figure2 , the sample consists mainly of prime-age laborers with a moderate proportion of younger farmers, suggesting that new technologies like agricultural drones may spread more readily within this demographic.

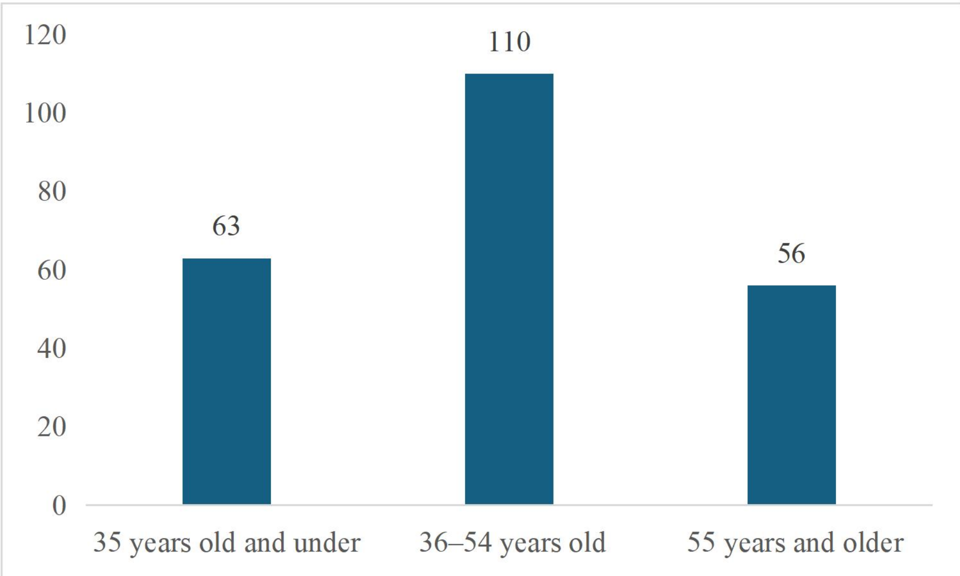

Figure2 Age distribution of survey respondents

(3) Educational Background Distribution

Regarding educational attainment, junior high school or below dominated at 52.84% (121 cases), senior high school/vocational school accounted for 30.57% (70 cases), while college or above represented only 16.59%(38 cases). As shown in Figure and3 , the educational reflects the typical characteristics of a rural sample. This suggests that when promoting drones, emphasis should be placed on providing simple and easy-to-understand operational training to reduce the constraints on acceptance posed by educational barriers.

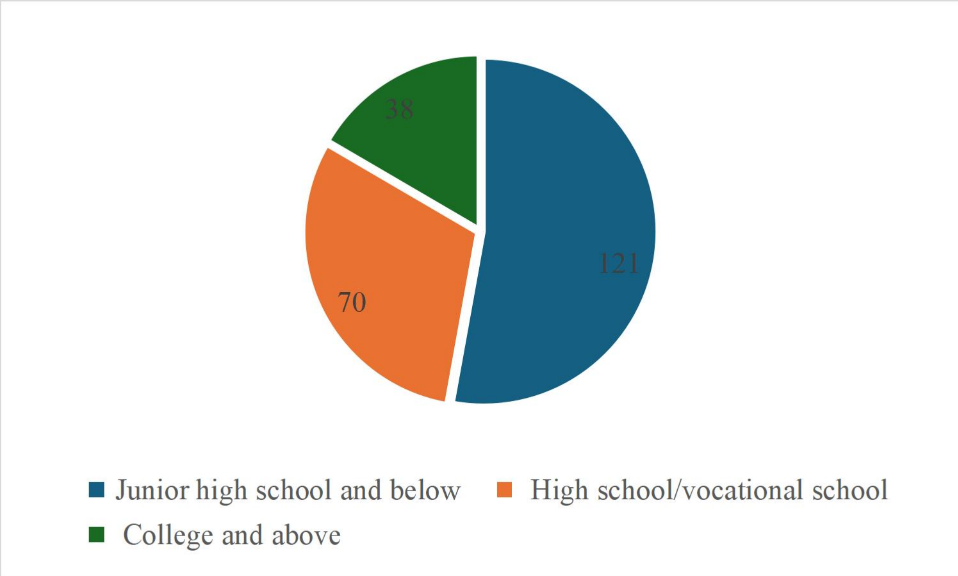

Figure3 Educational Attainment Distribution of Survey Respondents

(4)Analysis of Agricultural Operation Scale

A gricultural operation scale is predominantly concentrated in small-to-medium sizes: 51.53% (118 cases) operate 50-100 mu, 31.00% (71 cases) operate under 50 mu, and 17.47% (40 cases) operate over 100 mu. As shown in Figure4, the sample primarily consists of small-to-medium-sized farmers with few large-scale operators, making it suitable for evaluating the applicability of drones in precision operations.

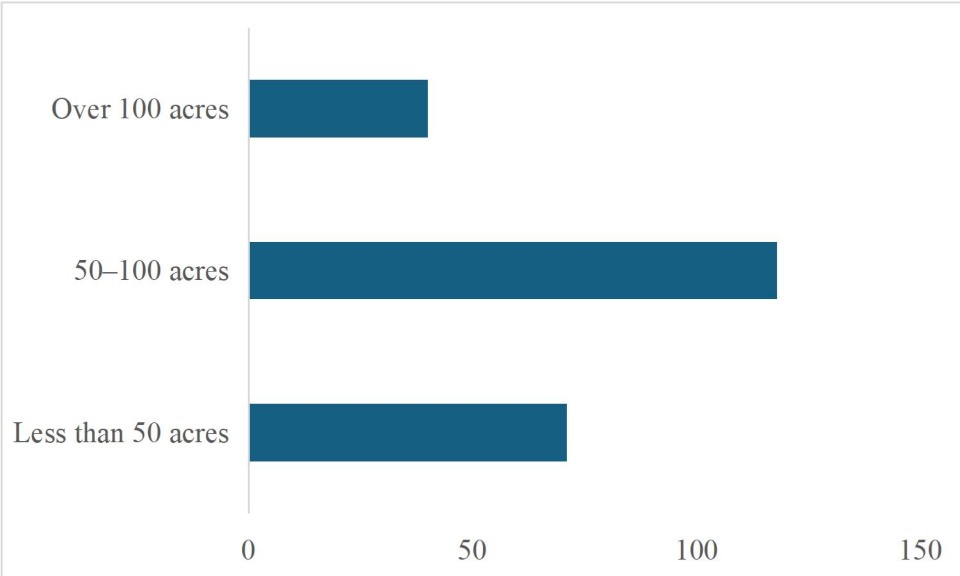

Figure4 Farming Scale of Surveyed Households

(5)Engagement in Non-Agricultural Work

Regarding non-agricultural work (side jobs), 59.39% (136 cases) of respondents engaged in side jobs, while 40.61% (93 cases) were purely agricultural. As shown in Table1 , the relatively high proportion of side-job farmers reflects the reality of diversified rural labor, which may impact their time commitment to and willingness to adopt new technologies.

Table1 : Whether Survey Participants Engage in Non-Agricultural Work

Item	Option	Sample Size	Proportion (%)
Non-agricultural work (part-time)	Yes	136	59.39
	No	93	40.61

Item	Option	Sample Size	Proportion (%)
Total		229	100.00

Overall, this sample represents typical characteristics of Chinese rural households, primarily consisting of young and middle-aged individuals with junior high school education who engage in part-time farming on small to medium-sized plots. It demonstrates strong representativeness and provides a solid foundation for exploring factors influencing the adoption of agricultural drones.

3 Empirical Analysis

3.1 Reliability Analysis

Reliability testing, also known as validity testing, uses Cronbach's Alpha coefficient to indicate data stability. A coefficient closer to 1 signifies higher reliability. A value above 0.8 indicates high reliability for the scale data. A Cronbach's Alpha coefficient below 0.6 suggests that scale items require modification.The specific results of the reliability test in this study are shown in the table below. As indicated by Table2 , the Cronbach's Alpha value of the scale is 0.952, exceeding the reliability threshold of 0.8, confirming good data reliability.

Table2 Reliability Test Table

Number of Items	Cronbach's Alpha Coefficient
20	0.952

3.2 Validity Analysis

Validity reflects the effectiveness of a measurement tool; a higher value indicates stronger consistency between the measured content and the target characteristics. The KMO test is used to assess questionnaire validity, with values ranging from 0 to 1. A value closer to 1 indicates better suitability for factor analysis. A KMO value exceeding 0.7 indicates data suitability for factor analysis, while a value below 0.5 is not recommended.The KMO value for this study's scale is 0.968 (see Table7), demonstrating the questionnaire's strong validity and reliability.

Table3 Validity Test Table

KMO Value		0.968
Bartlett's Sphericity Test	Approximate Chi-Square	2636.307
	df	190
	p-value	0.000

3.3 Descriptive Statistics

This study conducted descriptive statistical analysis on the mean scores of the five core dimensions of the UTAUT model (performance expectancy, effort expectancy, social influence, policy support, and acceptance readiness) using a sample of 229 valid questionnaires.These variables were calculated using a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree). Mean scores above 4 indicate overall positive attitudes among farmers. The median score of 5.25 further confirms that most respondents tended to "agree" or "strongly agree," providing a solid data foundation for subsequent model validation.

As shown in4 at Specifically, the dimension of smallholder acceptance willingness scored highest (mean 4.782, SD 1.474), indicating the strongest willingness among farmers to purchase, recommend, and learn drone technology in the future. This reflects robust latent market demand, potentially driven by anticipated practical benefits.Performance expectations (mean 4.723, SD 1.532) and social impact (mean 4.719, SD 1.505) ranked next. Farmers recognize drones' potential to enhance efficiency and reduce costs, driven by social demonstration effects. However, moderate variability (SD ~1.5) indicates individual cognitive differences, possibly related to farm scale or experience.Effort Expectations (mean 4.674, SD 1.472) scored lowest, with slightly weaker perceived operational ease and the smallest standard deviation, indicating high consensus. Policy Support (mean 4.709, SD 1.558) showed the greatest variation, suggesting that external incentives like subsidies and training affect different farmers differently.

Table4 Descriptive Statistics Analysis Table

Variable	N	Mean	Standard Deviation
Performance Expectations	229	4.723	1.532
Striving for Expectations	229	4.674	1.472
Social Impact	229	4.719	1.505
Policy Support	229	4.709	1.558
Willingness to Accept	229	4.782	1.474

3.4 Correlation Analysis

As shown in Table5 at , the Pearson correlation matrix for the five variables—performance expectancy, effort expectancy, social influence, policy support, and acceptance willingness—displays correlation coefficients. The ** in the upper right corner indicates significant correlation at the p<0.01 level.All correlation coefficients between variables range from 0.758 to 0.846, indicating strong positive correlations. Performance Expectation shows the highest correlation with Policy Support (0.846), Effort Expectation with Social Influence (0.796), and Policy Support with Acceptance Willingness (0.815).Overall, the four factors—performance expectancy, effort expectancy, social influence, and policy support—are all closely and positively associated with acceptance willingness. However, the high correlations among variables also indicate a risk of multicollinearity. If subsequent empirical studies such as regression analysis are conducted, this issue should be tested and addressed using metrics like the variance inflation factor.

Table5 Correlation Analysis Table

Variable	Performance Expectation	Effort Expectation	Social Influence	Policy Support	Willingness to Accept
Performance Expectations	1				
Effort Expectations	0.758**	1			
Social Influence	0.777**	0.796**	1		
Policy Support	0.846**	0.762**	0.830**	1	
Willingness to Accept	0.822**	0.756**	0.798**	0.815**	1

* p<0.05 ** p<0.01

3.5 Regression Analysis

As shown in Table6 at REF _Ref220263878 \h , this study employed a multiple linear regression model to examine the predictive effects of performance expectancy, effort expectancy, social influence, and facilitating conditions on farmers' intention to use agricultural drones under the UTAUT theoretical framework.Results indicate the model exhibits good overall fit (R^2=0.757, adjusted R^2=0.753) with a significant F-test (F=174.454, p<0.001). This demonstrates that the four dimensions collectively explain 75.7% of the variance in behavioral intention, robustly validating the explanatory power of the UTAUT model in agricultural technology adoption contexts.The Durbin-Watson statistic was 1.911, close to the ideal value of 2, indicating no significant autocorrelation in residuals. All variable VIF values were below 5 (maximum 4.853), ruling out multicollinearity interference and ensuring robust coefficient estimates.

Regarding predictive contribution, all independent variables exerted significant positive effects on behavioral intention (p<0.05).Performance Expectation exhibited the most pronounced effect (standardized coefficient β=0.35, p<0.001). Each one-unit increase in perceived performance raised behavioral intention by 0.337 units. This highlights that perceived benefits of drones in enhancing operational efficiency and reducing costs serve as the core driver of farmer decision-making, consistent with UTAUT theory's classic conclusion that performance expectation is the strongest predictor. Social Influence (β =0.235,p=0.001) and facilitating conditions (β =0.219, p=0.003) followed, indicating significant influence from recommendations by friends and relatives, cooperative encouragement, and subsidy services . Effort expectancy (β =0.137, p=0.021) showed relatively weaker impact, possibly due to low perceived barriers to drone operation among farmers.

Table6 Regression Analysis Table

	Unstandardized Coefficients		Standardized Coefficient			Multicollinearity Diagnosis	
	B	Standard Error	Beta	t	Significance	VIF	Tolerance
Constant	0.488	0.172	-	2.838	0.005	-	-
Performance Expectations	0.337	0.063	0.35	5.314	0.000**	3.994	0.25
Social Impact	0.137	0.059	0.137	2.322	0.021*	3.195	0.313
Policy Support	0.23	0.065	0.235	3.524	0.001**	4.105	0.244
Effort Expectation	0.207	0.069	0.219	3.022	0.003**	4.853	0.206

R^2 = 0.757, adjusted R^2 = 0.753, F(4,224) = 174.454, p = 0.0, DW = 1.911, N = 229

* p<0.05 ** p<0.01

4 Discussion of Results

This study examined the influence of performance expectations, effort expectations, social influence, and policy support on the acceptance intention of agricultural drones among smallholder farmers in Liaoning Province based on the UTAUT model. Combining empirical data with survey findings, the following key conclusions were drawn:

4.1 Performance Perception is the Primary Driver

Smallholder farmers prioritize the practical benefits of agricultural technologies. Drones' advantages—reducing labor requirements, improving pesticide utilization efficiency, and lowering production costs—precisely address core challenges faced by Liaoning's smallholders, such as labor shortages and rising labor costs.Regression analysis reveals that the standardized coefficient for performance expectancy is β=0.35—the highest among the four variables—indicating its most significant positive impact on adoption willingness. This aligns with relevant domestic and international empirical research findings and validates the classic assertion in UTAUT theory that performance expectancy is the core predictor of technology adoption.

4.2 Significant influence of social environment

Smallholder production decisions are highly influenced by surrounding groups. The usage experiences of relatives, friends, and neighbors, along with demonstration and promotion efforts by cooperatives and village officials, effectively reduce smallholders' unfamiliarity and concerns about drones. Case studies in Dalian and other areas indicate that methods such as on-site demonstration operations and farmer experience sharing can rapidly increase smallholders' acceptance of drones.Data analysis reveals that the standardized coefficient for social influence (β=0.235) exerts a positive effect on adoption intent second only to performance expectations. This underscores the powerful driving force of demonstration effects within the context of rural familiar-society networks.

4.3 Policy Support is Indispensable

Policies such as subsidies and training directly reduce the cost and technical barriers for smallholder farmers to adopt drones. Regression results show that the standardized coefficient for policy support (β=0.219) has a significant positive impact on adoption willingness. However, field research indicates that while drone-related training has been implemented in some areas of Liaoning Province, its coverage remains limited. Most smallholder farmers lack sufficient awareness of subsidy policies, preventing the full realization of policy support's positive effects.Given that the standard deviation for policy awareness was the highest (1.558) in descriptive statistics, it is evident that perceptions of policies vary significantly among farmers. There remains considerable room for improvement in policy implementation and outreach.

4.4 Perceived ease of operation has a relatively weak impact

Among the four variables, effort expectation exhibits the weakest positive influence on smallholder farmers' willingness to adopt agricultural drones, with a standardized coefficient of only 0.137. This stems primarily from the severe aging of Liaoning's smallholder farming population (48.5% aged 55 and above), where most farmers possess limited learning capacity and prefer outsourcing drone services over purchasing and operating equipment themselves. Consequently, they pay less attention to operational complexity and learning costs.Furthermore, descriptive statistics reveal that the mean effort expectation of 4.674 is the lowest among the five variables, accompanied by the smallest standard deviation (1.472). This indicates a convergence in farmers' perceptions of drone operational difficulty, further diminishing its influence on adoption willingness.

5 Countermeasures and Recommendations

5.1 Highlight the practical benefits of agricultural drones and strengthen performance-based awareness guidance

Governments and agricultural enterprises should collaborate on diversified promotional activities. Through regular field demonstrations and case studies highlighting typical benefits, they should vividly showcase the advantages of agricultural drones in core operations such as plant protection, seeding, growth monitoring, and pest/disease early warning.For Liaoning's dominant grain crops like corn and rice, tailor-made drone operation plans should be developed based on specific growth stage requirements. Examples include precision seeding during rice seedling cultivation and efficient pest control during corn grain filling. Clearly articulate efficiency gaps between drone operations and traditional manual/small-scale mechanical methods—such as drones covering 80-120 mu (5.3-8 hectares) per day for pest control, 15-20 times faster than manual labor,while reducing pesticide loss by 15%-20%, significantly lowering input and labor costs. By distributing benefit comparison manuals, conducting on-site cost-benefit calculations, and inviting beneficiary farmers to share their experiences, smallholder farmers gain tangible awareness of the economic gains from technology. This approach dispels misconceptions like "technology is useless" or "costs are too high," enhancing their willingness to adopt these innovations[5] .

5.2 Establishing a Socialized Promotion Network to Amplify Demonstration Effects

Leveraging grassroots agricultural service systems, we fully utilize the organizational strengths of agricultural cooperatives, the coordination capabilities of village cadres, and the exemplary role of large-scale growers. Agricultural drone demonstration and promotion sites are deployed in townships and administrative villages to extend service coverage to rural areas.Regularly organize on-site observation activities for smallholder farmers, allowing them to closely observe drone operation processes and outcomes. Concurrently hold experience-sharing sessions where demonstration households share drone operation techniques, field insights, and income changes. Leveraging the trust foundation and word-of-mouth characteristics of rural communities, this approach effectively reduces smallholders' unfamiliarity and concerns about adopting new technologies.Establish a demonstration household support mechanism, encouraging these households to form assistance partnerships with neighboring farmers. Provide services such as free trials and hands-on guidance to create a virtuous promotion pattern where "one household drives a cluster, and multiple clusters radiate across the entire area," accelerating technology penetration among smallholder farmers[6] .

5.3 Optimize the policy support system to enhance policy implementation and awareness

Further refine agricultural drone purchase subsidy policies by expanding coverage to include all small-to-medium-sized, cost-effective drones suitable for Liaoning's staple crops. Adjust subsidy ratios to align with smallholder farmers' economic capacity, substantially lowering purchase barriers and initial investment costs.Addressing the characteristics of Liaoning's smallholder farmers—relatively low educational attainment, high aging rates, and limited capacity to adopt new technologies—optimize technical training and guidance models. Replace lectures laden with technical jargon with a combination of "hands-on instruction + field classroom practice." Technicians should demonstrate operational procedures and troubleshooting methods on-site to ensure farmers can learn and master the skills effectively.Simultaneously, policy outreach channels have been expanded. Through diverse methods—including posters on village bulletin boards, explanatory content shared in village WeChat groups, offline presentations by township agricultural technicians, and leaflet distribution at local markets—policy information such as subsidy standards, application procedures, and training schedules is precisely delivered to every household[7]. This approach bridges the "last mile" of policy implementation, enhancing farmers' awareness and sense of benefit.

5.4 Refining Drone Service Models to Lower Operational Barriers

Addressing the practical needs of small-scale farmers who are reluctant to purchase drones independently or lack operational skills, actively guide agricultural enterprises and cooperatives to expand flexible service models such as drone operation services, short-term rentals, and per-acre fee structures. This allows farmers to access drone services without purchasing equipment, meeting fragmented and low-cost operational demands.Encourage drone manufacturers to optimize product design by simplifying interfaces and adding user-friendly features for elderly farmers, such as one-touch start/stop, voice navigation, and preset flight paths. This reduces operational complexity and improves accessibility.Simultaneously, establish a comprehensive after-sales maintenance service system covering county, township, and village levels. Set up repair stations in key townships, staffed with professional technicians and equipped with common spare parts[8]. Offer services including on-site inspections, emergency repairs, and regular maintenance to promptly resolve repair issues encountered by smallholder farmers during equipment use. This will completely eliminate their concerns about "not knowing how to repair" or "unaffordability of repairs," enabling smallholder farmers to use the equipment with confidence.

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