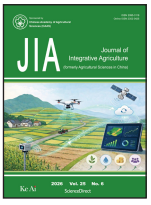
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RESEARCH ARTICLE

Farmers' preferences for agricultural drone services under uncertainty: A choice experiment in Hubei, China

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Highlights

- Small farmers are willing to adopt agricultural drone services when collective hiring is feasible.
- Farmers prefer drone services provided by local suppliers with contracts.
- Farmers who are younger, with higher-education, and have prior adoption experiences are more likely to adopt drone services.

Abstract

Agricultural drones can improve productivity, save labor, and reduce environmental impacts by offering digital multifunctionality in agricultural production. Yet, the lagging adoption among smallholders is still prevalent. Existing literature commonly explains it by the lack of capital, land fragmentation, and digital illiteracy, with little delving into specific adoption modes under uncertainty. In this study, we demonstrate the potential of hiring agricultural drone services and investigate the role of supplier uncertainty in the adoption decision. We conduct a discrete choice experiment among 338 farmers in Hubei Province, China. Mixed logit models are used to analyze farmers' preferences for the agricultural drone service (ADS) and its attributes. The results show that the large majority of sampled farmers are willing to adopt ADS. Besides low prices, farmers prefer services with local suppliers and contracts. Potential adopters in this choice experiment are characterized by youth, higher education, owning poor-topography farms, drone learning *via* word-of-mouth, and adoption experience. The willingness to pay analysis indicates that farmers would like to spend 25 CNY per mu (53 USD per ha) on average for ADS. Notably, farmers value the localness of suppliers more than the form of agreements when choosing a particular drone service. These findings suggest that the mode of hiring ADS can effectively motivate farmers' adoption intention, thereby requiring supply-side incentives and uncertainty-reducing promotion strategies to enhance smallholders' access to and adoption of agricultural drones.

Keywords: UAV, digital agriculture, technology adoption, mixed logit model

1. Introduction

Digitalization has been considered a technological revolution in agriculture, contributing to productivity growth and environmental sustainability (Gabriel and Gandorfer 2023). A suite of digital technologies is emerging to support data-driven intelligent farming management and a higher degree of automation in production operations. Notably, drones, also known as unmanned aerial vehicles (UAVs), have been applied in different stages of crop farming. In 2016, the global market value of agricultural drones was estimated at 32.4 billion USD, with a brisk annual growth rate projected (Sylvester 2018). In practice, drones equipped with sensors or tanks can collect highly accurate data to monitor the real-time growth of crops and facilitate the precision use of inputs like seeds, pesticides, fertilizer, etc. (Quan *et al.* 2023). With the advancement of multirotor drones, this technology can accommodate various terrains, which opens up the potential for operating drones on small farms. Given the digital multifunctionality, drones are deemed to play an essential

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role in the precision farming and agricultural digitalization transition.

While there is a growing body of literature on the adoption of digital technologies in agriculture, studies specifically focusing on drone uptake remain limited. The existing research on this topic can be categorized into two major strands. One strand broadly explores determinants of usage intention along selected case studies. The other stream approaches to dissect actual adoption behaviors and decision processes. More specifically, Zheng *et al.* (2019) use a Probit regression model to identify determinants of drone adoption for pesticide application among Chinese farmers. Their results underscore the positive relationship between farmers' adoption intention and perceived technical characteristics, e.g., understanding of new technology, perceived ease-of-use, and usefulness. Wachenheim *et al.* (2021) further analyze the role of social networks. They find that family relations with a village cadre and available borrowing channels can drive adoption decisions, whereas cooperative membership and relationships with fellow villagers have no significant effect. However, Skevas and Kalaitzandonakes (2020) and Chen *et al*. (2020) argue that farmers who participate in cooperatives are more likely to be adopters. A study conducted among Australian farmers shows that education, farm size, and financial stress can potentially influence the uptake of agricultural drones (Zuo *et al.* 2021). Nevertheless, the above studies neither specify the adoption mode, i.e., purchasing or hiring, nor pay adequate attention to smallholder farmers. Another literature strand focuses on identifying adoption behavior. Based on a *trans*-theoretical model, Michels *et al.* (2020) measure the adoption of drones as a four-stage progression to gain a deeper insight into how farmers' socio-demographics affect each stage. Concerning the intention-behavior gap, a recent study in Germany provides empirical evidence that farmers' behaviors of adopting drones can be predicted by their intention to use drones (Michels *et al.* 2021). This lays the foundation for the ex-ante analysis of adoption. Using a contingent valuation method, Parmaksiz and Cinar (2023) explore farmers' preferences for agricultural drone rental by directly asking their willingness to pay.

Following this line of research, we elicit farmers' decision-making on hiring agricultural drone services (ADS) in smallholder farming systems along a discrete choice experiment (DCE). In contrast to the previous literature, we concentrate on the specific adoption mode of outsourcing agricultural drone operations, especially in the context of small-scale farms. Following the FAO (2013) definition, smallholders in this study are defined as farmers operating no more than 10 hectares of cropland. For such smallholder farmers, the upfront investment — including device cost and learning cost — is typically too high to operate agricultural drones themselves. Hiring ADS is expected to enable them to access drone offerings without substantial adoption costs. Despite this, outsourcing comes with principal-agent problems. From the standpoint of farmers, uncertainty about supplier behavior in operating drones would largely affect their benefit evaluation and thus change their adoption decisions. This motivates us to incorporate supplier uncertainty into the experiment of behavioral simulation and discuss the roles of different supplier attributes. Heterogeneity in farmer's characteristics is also important to consider, as China's agriculture has a large population of smallholder farmers with highly diverse endowments. Understanding these differences can help develop tailored extension strategies and effective policy interventions.

The primary objective of this paper is to investigate farmers' preferences for agricultural drone services in smallholder farming systems. In particular, we strive to answer three research questions: 1) Are smallholder farmers willing to adopt agricultural drone services on the premise of collective adoption? 2) How does the supplier uncertainty affect farmers' choices on ADS? 3) How is the preference heterogeneity shaped by individual, household, and farm characteristics? To this end, we model farmers' decision to adopt ADS in an experimental setup where farmers need to make tradeoffs between ADS alternatives and their specific attributes, as in an actual market. This would help to improve the reliability of measurement for adoption intention, compared to asking for a binary decision. We use mixed logit models to estimate farmers' preferences and conduct willingness to pay (WTP) analysis to quantify the monetary value of ADS and its attributes.

Our research adds insights to the drone adoption literature from the lens of hiring ADS in smallholder farming systems. More specifically, first, we underscore that ADS could be an organizational innovation that allows a group of small farmers to collectively hire drones to fly over their plots. Unlike purchasing drones, hiring drone services requires neither a fixed investment in hardware nor learning costs of operation skills. Collective hiring of drone services relaxes the farm scale dependence and, thus, becomes one of the few options for smallholders to participate in the digital technology transformation. Additionally, we provide the first experimental evidence of the links between supplier uncertainty and ADS uptake by investigating the importance of supplier-buyer proximity and service quality assurance in a choice experiment. In this study, we select the localness of suppliers and the form of agreements as ADS attributes and create different combinations of their attribute levels to represent various extents of uncertainty in adoption. As such, we can identify the effect of supplier uncertainty on adoption decisions and quantify the monetary compensation for uncertainty reduction.

2. Agricultural drones in China

In the past decades, China's agricultural drone industry has been undergoing rapid development supported by government policies. In 2010, the first drone was produced for crop protection, kicking off a new chapter in commercializing agricultural drones in China. Subsequently, guided by national programs related to accelerating land transfer (SCC 2014), reducing the use of agrochemicals (MOA 2015), and improving agriculture modernization (SCC 2016), a large number of manufacturers, such as DJI and XAG, have surged into the field of agricultural drones, fueling the R&D of agricultural drone technology and achieving its

large-scale production. Over the same period, Chinese policymakers have launched local and nationwide subsidy schemes to stimulate the demand of end-users, i.e., agricultural producers. According to statistics compiled from multiple volumes of the *China Agricultural Machinery Industry Yearbook* (CAMIA) (2015–2023), from 2014 to 2022, the number of agricultural drones in operation increased from 461 to 130,719, while the treated acreage of plant protection rose from 2.26 to 22.54 million ha (CAMIA 2023). Notably, CAMIA 2015–2018 only reports data on agricultural aircraft, which may include manned aircraft, whereas statistics in CAMIA 2019–2023 specifically refer to plant protection UAVs, which account for over 98% of agricultural aircraft. China has become one of the world's dominant drone manufacturing and application markets.

Compared to conventional agricultural practices, drones are highly valued for their efficiency, flexibility, and safety. Using pesticide spraying as an example, the daily operation area of a drone is 300–500 mu, 30–60 times that of manual operation (Zheng *et al.* 2019). Furthermore, the downwash airflow generated by rotors can improve the deposition distribution of spray droplets and enhance the application efficiency of pesticides. An agricultural drone can save 30–50% of pesticides and 90% of water, thus reducing the adverse impact on the environment (Scherer *et al.* 2017). In terms of health benefits, the remote control avoids operators' exposure to toxic agrochemicals and ensures the safety of spraying work. With the extension of functions and application scenarios, agricultural drones can also conduct seeding, irrigation, and farmland information monitoring, notably in rice farming, where these advantages stand out and could be widespread. Nevertheless, the current beneficiaries are mainly large farms, farm cooperatives, or agricultural companies, as observed in many studies. Small farms are restricted from tapping the technical and economic benefits due to high fixed investment and learning costs (Michels *et al.* 2021). It is simply not practical and economical for most smallholders to purchase drones to serve their farms, which are less than 1 ha land size on average and often break down into a number of even smaller, spatially scattered plots.

Against the backdrop, the agricultural drone services delivered by professional teams, such as companies and cooperatives, have emerged as a feasible solution to overcome these barriers. Small farmers can collectively hire drone services, as long as their plots are spatially agglomerated and grow the same crops. Although this activity is still in the early stage of exploration, it is expected to become one of the major adoption trends in the future. Given the development of agricultural drones and the circumstance of smallholder agriculture, China can offer a particularly interesting and meaningful case study on the adoption of agricultural drone services, which may also reveal new insights for many other developing countries dominated by smallholder farming systems.

3. Data and methods

3.1. Choice experiment design

A discrete choice experiment (DCE) is a useful method to ex-ante assess farmers' underlying preferences for ADS, as this mode of adoption has not been widely applied in the study area so far. In addition, there is a lack of studies based on the framework of a DCE to model drone adoption behavior, although DCE studies on other agricultural innovations can be found (Jaeck and Lifran 2014; Schulz *et al.* 2014; Oyinbo *et al.* 2020; Blasch *et al.* 2022). In this choice experiment, respondents were given hypothetical ADS scenarios in the form of choice cards and were asked to choose their most preferred option among three alternatives presented in each card. Choice experiments mimic actual market behavior where individuals need to make trade-offs among different levels of service attributes, subject to certain constraints (e.g., income). As such, the observed choices enable us to identify the role of specific attributes of ADS as well as farmers' willingness to adopt ADS; this is consistent with welfare economic theory (Champ *et al.* 2017).

Attributes and levels To generate a set of choice cards that depict the ADS with various uncertainties, we first identify the relevant attributes and their levels. We started with a literature review of this field, then consulted scientists within and outside the project team, and finally conducted a focus group discussion with farmers in Hubei. As shown in Table 1, three attributes were selected and included in the experiment design. According to the conceptual framework of Meijer *et al.* (2007), there are three key sources of external uncertainty for emerging technology adoption, namely political uncertainty, technological uncertainty, and supplier uncertainty. In the context of agricultural drones, political uncertainty refers to new institutional regulations to promote or inhibit the usage of agricultural drones, such as subsidies and flight bans. Technological uncertainty is associated with the characteristics of the new technology. In reality, however, farmers are relatively passive when it comes to these two types of uncertainty, especially in the early diffusion of innovations (Glover *et al.* 2019). Given their limited technical knowledge of agricultural drones, it is hard for farmers to disentangle and consider the details of the technology. Our focus group discussion indicated that farmers would choose the drone alternative only if it had higher effectiveness than manual spraying. On the other hand, farmers felt indifferent to the subtle variation (normally at the minute level) in spraying efficiency between two drones. Therefore, we assumed no variations in terms of the political background and the technical traits and placed our focus on supplier uncertainty.

Supplier uncertainty was regarded by stakeholders as a crucial element in hiring decisions. This is intuitive because in the case of outsourced ADS, farmers' decisions become

Table 1 Attributes and levels for agricultural drone services (ADS)

Attributes	Levels
Localness of suppliers	Local service supplier
	Nonlocal service supplier
Form of agreements	Contractual agreement
	Oral agreement
Service price (CNY mu^{-1})[1)]	8, 10, 12

[1)] 1 ha=15 mu.

more dependent on the reliability of suppliers. When farmers lack knowledge of, or confidence in, supplier actions, that is, when they perceive high supplier uncertainty, farmers will show low intention to adopt the technology. With this in mind, we listed and ranked the attributes. It shows that farmers' perception of supplier uncertainty is mainly anchored on geographic proximity and agreement binding.

We use the localness of service suppliers to denote the geographic proximity between buyers and suppliers. Proximity fosters trust and facilitates communication (Kabirigi *et al.* 2022). Additionally, agriculture is a geographically localized phenomenon, and knowledge of local natural resources, such as climate, soil, and topography, helps reduce the uncertainty of outcomes. In the choice card, we presented the attribute as whether the service supplier came from the county and coded it with a dummy variable.

Agreement binding is associated with the uncertain quality of service performance: if the service supplier does not live up to the agreement and performs poorly, it would cause uncertainty for farmers. To control opportunistic behavior, people tend to clarify the expected performance and latent risk in a certain way, typically through oral or contractual agreements. While oral agreements are more flexible and need lower transaction costs, contractual agreements provide stronger service quality guarantees and clearer legal protection (Abebe *et al.* 2013). In this study, we use the form of agreement to represent uncertainty in service quality assurance that farmers are likely to face. We coded this attribute as 1 for a contractual agreement and 0 for an oral agreement.

To evaluate the economic magnitudes of these two attributes, we add the price per mu (1 ha=15 mu) of ADS as the last attribute. It is determined based on the actual market price at the time of the survey, ranging from 8 CNY (1 USD≈ 7 CNY) to 12 CNY per mu.

In China's agricultural socialized services, an increasing number of suppliers are incorporating drone services into their service packages at present. According to the latest 24 Model Cases of "Full-Process Mechanization+Integrated Farming Services", 15 suppliers offer ADS, 10 of which operate locally (MARA 2021). Since ADS are typically bundled with other segment services, most are contract-based, with only one case explicitly indicating the use of oral agreements for individual services. In our survey, 97% of adopters used individual ADS with oral agreements, and the ADS suppliers were from the county. Considering these service attributes in reality, we would like to understand farmers' trade-offs in choosing one alternative over another.

Choice cards and experimental design To allocate the attribute levels into choice cards and develop an efficient design, we first conducted a pilot survey of the DCE with 42 farmers, in which the choice cards were generated by an orthogonal design with all zero priors (Burgess and Street 2005). Using the data from the pilot DCE, a mixed logit model was estimated, and the parameters were applied as Bayesian priors with the assumption of normal distribution for the ultimate D-efficient design in Ngene®.

According to the efficient design, we constructed eight choice cards divided into two blocks, each with four cards, a reasonable number with an appropriate cognitive load for respondents (Street *et al.* 2007). Each choice card consists of two unlabeled hypothetical options for ADS and an opt-out indicating no drone service. The opt-out option is included to simulate a real application where farmers are able to freely decide to hire ADS. It is noted that the choice experiment is framed under the hypothetical situation where collective hiring ADS is feasible, aiming to better capture farmers' actual uptake intention. During our pretest, we observed that farmers with extremely small farms (e.g., less than 10 mu) tend to exclude themselves from the choice experiment. This is because, in practice, even if these farmers are willing to adopt the service, ADS teams rarely serve them for the sake of cost-effectiveness. To mitigate the selection bias because of the prior experience, we implicitly assume that farmers are allowed and able to hire drone services collectively. Pictograms were used to enhance the readability of the choice cards. After creating the design, the respondents were randomly assigned to one of the two blocks. The four choice cards of the block were presented to respondents by enumerators in a random order to mitigate potential ordering effects (Loureiro and Umberger 2007). Fig. 1 shows an example of a choice card in this study.

In this experimental design, we did not include additional minor attributes or more choice cards so as to ensure that farmers understand the meaning of each card and can make adequate trade-offs between all attributes of alternatives. This is quite essential to develop appropriate individual utility functions and improve the validity of our measurement in the context of rural areas (Caputo *et al.* 2018). Additionally, aligning with extant literature, we assume that individual-specific characteristics (e.g., socio-demographics, farm characteristics, and technology literacy) play an important role in the adoption decision, thereby shaping preference heterogeneity. In brief, we illuminate farmers' adoption decisions through the lens of supplier uncertainty but also incorporate individual-specific characteristics into our analysis framework, which is outlined in Fig. 2. Correspondingly, our following econometric farmwork will be built on this.

3.2. Econometric framework

In the DCEs, individuals are asked to indicate their preferred option from a set of hypothetical alternatives described by underlying attributes. In this process, individuals, assumed

	Alternative 1	Alternative 2	Opt-out
Localness	 Local supplier	 Non-local supplier	None of the above
Agreement	 Contractual agreement	 Oral agreement	
Price (CNY mu^{-1})	10	8	
I prefer			

Fig. 1 Choice card example (original cards are in Chinese during survey).

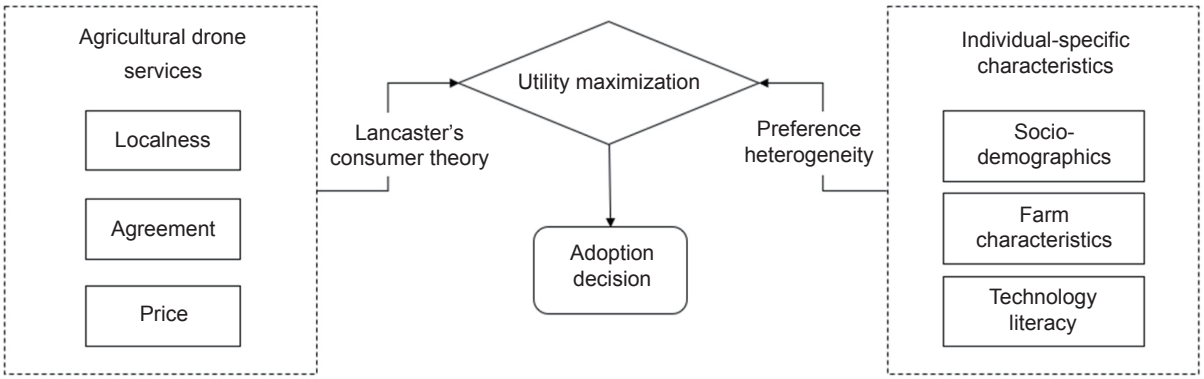


Fig. 2 Factors associated with the adoption decision of agricultural drone services (ADS) based on literature review.

to be utility maximizers, are expected to make the choice that offers the highest utility among the set of alternatives (McFadden 1972). It is assumed that the obtained utility is derived from the attributes of the alternative rather than the alternative per se (Lancaster 1966). In line with this, the combinations of attributes portray the structure of tastes or preferences of decision-makers. The intensity of those preferences is embodied in the latent utilities, allowing the prediction of the choice probability (Hensher *et al.* 2015).

In the choice experiment setting, we assume that the utility of farmer $i \in \{1,\ldots,n\}$ perceived by choosing alternative $j \in \{1,\ldots,J\}$ in a choice set $s \in \{1,\ldots,S\}$ is given by U_{ijs}, consisting of an observed component, V_{ijs} and a residual unobserved component, ε_{ijs}. The observed component, V_{ijs}, depends on the attributes of the alternatives and characteristics related to the farmers. The unobserved component, ε_{ijs} captures the factors that affect utility but are not measured within V_{ijs} and not directly observable.

$$U_{ijs}=V_{ijs}+\varepsilon_{ijs} \quad (1)$$

Following McFadden's (1972) random utility framework, we map the latent utility functions to the choice probabilities. The probability that farmer i chooses alternative j in the choice set s is denoted as:

$$\begin{aligned} Prob_{ijs} &= Prob(U_{ijs}>U_{iks}, \forall\, k\neq j) \\ &= Prob(V_{ijs}+\varepsilon_{ijs}>V_{iks}+\varepsilon_{iks}, \forall\, k\neq j) \\ &= Prob(\varepsilon_{ijs}-\varepsilon_{iks}>V_{iks}-V_{ijs}, \forall\, k\neq j) \end{aligned} \quad (2)$$

The probability can be estimated by various econometric models which are induced under the specific assumption for the unobserved effects, ε_{ijs}. One restrictive form is the conditional logit model (CLM), where ε_{ijs} is assumed to be independent, identically distributed (IID), following a Gumbel (EV1) distribution. In this case, the parameters estimated in CLM are fixed over respondents, implying that all decision makers share the homogeneous preferences with each other (Hensher *et al.* 2015). As an extension of CLM, the mixed logit model (MXL) relaxes the restrictions for ε_{ijs} and assumes that the error terms remain independent but not identically distributed (Train 2009). That is, parameters in the choice model do not have to be fixed and are allowed to vary randomly across the population, so that we can further explore the preference heterogeneity (Train and Weeks 2005). In this light, our estimations start with the CLM and then extend to the MXL. We specify the utility function as a linear specification, such that:

$$U_{ijs}=\beta_0 ASC+\beta_1 localness_{ijs}+\beta_2 agreement_{ijs}+\beta_3 price_{ijs}+\varepsilon_{ijs} \quad (3)$$

The alternative specific constant (ASC) represents the utility of choosing opt-out in the choice sets, normalized to 1 for the "opt-out" alternative and 0 for others. A negative (positive) coefficient for ASC implies farmers derive lower (higher) utility from opting out compared to selecting one of ADS alternatives, showing more (less) preferences for adoption in a choice set. Including ASC allows for capturing unobserved sources of utility that are not explained by attributes present in the choice sets (Meyerhoff and Liebe 2009). $localness_{ijs}$ is a dummy variable assuming a value of 1 for local service suppliers and 0 for nonlocal service suppliers; $agreement_{ijs}$ is coded 1 when a contract is signed as a service quality assurance and 0 for oral agreement; $price_{ijs}$ represents the market price of ADS. β_n (n=0, 1, 2) and β_3 are estimated parameters to quantify farmers' preferences for ADS. We estimate the base model by firstly using CLM where all parameters are fixed, and then using MXL, assuming parameters for ASC, $localness_{ijs}$ and $agreement_{ijs}$ are random. As specified in eq. (2), only differences across alternatives can be identified since individual characteristics remain constant across alternatives. Therefore, we construct interaction terms to normalize at least one of the individual-specific variables to zero across alternatives, to shed light to the source of preference heterogeneity. The extended model is as follows:

$$\begin{aligned} U_{ijs}=&\beta_0 ASC+\beta_1 localness_{ijs}+\beta_2 agreement_{ijs} \\ &+\beta_3 price_{ijs}+\gamma x_{ijs} z_i+\varepsilon_{ijs} \end{aligned} \quad (4)$$

where z_i is a set of respondent characteristics including age, education level, cooperative membership, household income, off-farm labor, risk preference, farmland topography, contiguous plot size, drone learning channels, and adoption experience. x_{ijs} denotes a vector of the three variables with random parameters β_n (n=0, 1, 2). γ are the parameters of the interaction terms. The inclusion of interaction terms is crucial for helping explain differences in observed choices over the sampled population (Tao *et al.* 2024). Note that each MXL model in this paper is estimated with 2,000 Halton draws.

To further compare the relative importance of attributes, we calculate the marginal willingness to pay (WTP) between each non-monetary attribute and the price, according to the

results of the MXL in the base model.

$$WTP = -\frac{\beta_n}{\beta_3} \quad (5)$$

The WTP indicates the amount of money a respondent is willing to pay for a change in the attribute or the maximum price for the ADS adoption (Lundhede *et al.* 2009; Rommel and Sagebiel 2017; Kliem and Sagebiel 2023). We also estimate the subgroup WTPs to further explore preference heterogeneity. The confidence intervals of WTP estimates are constructed by using the Krinsky-Robb method with 10,000 draws.

3.3. Research area and sampling

The study area, Hubei Province, located in the middle reaches of the Yangtze River, is one of the largest agricultural provinces in China and is endowed with diverse terrains, including plains, hills, and mountains. Most regions of the province have a subtropical monsoon climate with advantageous light, water, and heat for agricultural production, especially for paddy rice production. In 2022, more than half of the total cropland (57.2%) in Hubei was sown with staple crops, with three major crops: rice, wheat, and maize, accounting for 92.4% of the area (HPSB 2023). On the other hand, according to the latest statistics, nearly 98% of agricultural producers in this province are smallholder farmers (NBSC 2018), which poses a challenge to the diffusion of agricultural drones.

We conducted a farm household survey in August 2023 in two counties, which were selected because of their variations in agroecological conditions and heterogeneous agricultural structures. Luotian, consisting of mountains and hills in northeastern Hubei, is dominated by smallholder farms. Honghu is situated in Jianghan Plain in the central south of Hubei, with fertile soil and relatively large croplands. Using stratified random sampling, 6 villages of Luotian and 8 villages of Honghu were selected based on the geographical distribution and socioeconomic development. Next, we randomly selected around 25 producers with crop production from a sampling frame provided by the village administration. We interviewed one (co-) decision-maker in farming management from these producer families. The entire interview was composed of two parts. The first part collected data on demographics, socioeconomic information, agricultural production, and experience with agricultural drones. The second part implemented a DCE after a brief introduction of attributes and levels. A team of enumerators was trained to conduct the face-to-face interview following a standardized and consistent procedure. In total, 338 effective interviews with crop farmers were undertaken, producing 4,056 observations for model estimation (i.e., 338×4×3).

Table 2 presents descriptive statistics of sampled farmers in this study. Respondents are 58 years old on average, with low education levels (only 20.2% received a high school education or above). Farmers who are risk-averse refuse to participate in an actual lottery, accounting for 34.0%, while others choose to join a lottery with different levels of risk, showing medium and high risk-seeking preferences, respectively. Of the farmers surveyed, 83.7% of households have at least one member engaged in off-farm work, and 20.1% of households are in cooperatives. The household income averages 69,411 CNY in 2022, with a large standard deviation. With regard to farm characteristics, there are 46.7% of farmers state that their farmland has relatively good topography compared to other farmland in the same village, and farmers evaluate it

Table 2 Sample characteristics and summary statistics (*n*=338)

Variables	Description/Unit	Mean	SD
Age	Age of the respondent farmers (years)	58.293	9.875
Education	1=below elementary school	13.6%	1.015
	2=elementary school	33.7%	
	3=middle school	32.5%	
	4=high school	17.2%	
	5=above high school	3.0%	
Risk preference[1)]	0=risk aversion	34.0%	0.817
	1=medium risk seeking	33.4%	
	2=high risk seeking	32.5%	
Off-farm	Member of household engaged in off-farm labor (1=yes, 0=no)	83.7%	0.370
Cooperative membership	Member of agricultural cooperative (1=yes, 0=no)	20.1%	0.401
Income	Household income in 2022 (1,000 CNY)	69.411	66.484
Farmland topography	1=good	46.7%	0.811
	2=medium	29.3%	
	3=poor	24.0%	
Contiguous plot	Size of the largest contiguous plot (mu)	5.887	8.281
Traditional media	Learned about agricultural drones *via* traditional media (e.g., TV, radio, and newspaper) (1=yes, 0=no)	15.4%	0.361
Digital media	Learned about agricultural drones *via* digital media (e.g., WeChat and TikTok) (1=yes, 0=no)	16.0%	0.367
Word-of-mouth	Learned about agricultural drones *via* word-of-mouth (1=yes, 0=no)	34.6%	0.476
Adoption experience	Adopted ADS before or not (1=yes, 0=no)	19.5%	0.397

[1)] Farmers' risk preferences are measured with real monetary pay-offs by asking farmers to choose: (1) take a fixed amount of 5 CNY (no risk); (2) join a lottery with a 50% chance of getting 10 CNY (medium risk); (3) join a lottery with 25% of getting 20 CNY (high risk). A higher choice number indicates more risk-seeking and *vice versa*.

as medium and poor at 29.3 and 24.0%, respectively. On average, the largest contiguous plot is 5.887 mu. Farmers have learned about agricultural drones through different channels, with 34.6% *via* word-of-mouth, 16.0% *via* digital media, and 15.4% *via* traditional media. In the study area, four-fifths of respondents have no experience in using ADS, even though the current ADS price is only around half the cost of labor input for the same agricultural operation. These characteristics have been demonstrated to be correlated with the adoption of other agricultural innovations (Dessart *et al.* 2019; Liu *et al.* 2021; Hadera and Tadesse 2023; Moritz *et al.* 2023; Qian *et al.* 2024), meanwhile, not been confirmed for hiring agricultural drone services.

4. Results

4.1. Choice model results

Table 3 reports the results of the conditional logit model and mixed logit models. The mean estimated coefficients for ADS attributes have consistent signs across these models,

Table 3 Results of conditional logit model (CLM) and mixed logit model (MXL)

	Model (1) CLM	Model (2) MXL	Model (3) MXL interacted	Model (4) MXL interacted	Model (5) MXL interacted
Mean estimates					
ASC[1)]	–2.798***	–10.022***	–10.965**	–9.916***	–9.942***
	(0.299)	(1.268)	(4.473)	(1.421)	(1.256)
Price	–0.172***	–0.403***	–0.401***	–0.404***	–0.401***
	(0.033)	(0.061)	(0.064)	(0.065)	(0.064)
Localness	0.777***	1.633***	1.623***	4.214***	1.632***
	(0.082)	(0.213)	(0.222)	(1.481)	(0.225)
Agreement	0.292***	0.562**	0.558**	0.566**	2.824
	(0.112)	(0.263)	(0.247)	(0.252)	(1.886)
Interaction terms			With ASC	With localness	With agreement
Age			0.137**	–0.040**	–0.026
			(0.059)	(0.018)	(0.023)
Education			–1.210**	0.067	0.424**
			(0.556)	(0.163)	(0.201)
Risk preference			0.046	0.140	0.178
			(0.591)	(0.192)	(0.256)
Off-farm			1.575	0.234	–1.303**
			(1.454)	(0.479)	(0.649)
Cooperative membership			–0.986	0.268	0.763
			(1.245)	(0.386)	(0.520)
ln(income)			–0.581	–0.237	–0.041
			(0.473)	(0.161)	(0.225)
Farmland topography			–1.281*	–0.183	–0.307
			(0.666)	(0.183)	(0.253)
Contiguous plot			–0.011	0.013	–0.017
			(0.076)	(0.029)	(0.031)
Traditional media			–0.094	–0.885	0.353
			(1.477)	(0.559)	(0.724)
Digital media			1.244	0.824	0.168
			(1.588)	(0.584)	(0.727)
Word-of-mouth			–1.684*	1.056***	–0.328
			(1.014)	(0.340)	(0.430)
Adoption experience			–2.366*	–0.205	–1.415**
			(1.432)	(0.454)	(0.614)
Standard deviation estimates					
ASC		5.969***	5.554***	5.820***	5.894***
		(0.943)	(1.033)	(1.041)	(1.033)
Localness		2.176***	2.151***	2.049***	2.198***
		(0.242)	(0.241)	(0.241)	(0.246)
Agreement		2.829***	2.788***	2.866***	2.644***
		(0.332)	(0.359)	(0.372)	(0.356)
Observations	4,056	4,056	4,056	4,056	4,056
AIC	2,402.966	1,962.083	1,957.826	1,961.795	1,962.302
Log-likelihood	–1.2e+03	–974.041	–959.913	–961.897	–962.151

[1)] ASC, alternative specific constant.
Standard errors in parentheses. *, $P<0.1$; **, $P<0.05$; ***, $P<0.01$.

confirming that the estimates are robust to changes in the estimation model. Compared to the CLM, the MLX models have better goodness-of-fit according to the AIC and log-likelihood, so we primarily base our discussion on the MLX estimations.

The negative and statistically significant coefficient for ASC indicates that opting out would result in negative utility for farmers. To maximize their utility, farmers tend to adopt one of the alternative drone services in a choice set, instead. In the survey, only 5% of farmers never choose ADS, suggesting that the large majority of sampled farmers prefer ADS over no adoption, on the basis of the collective adoption premise. As expected, the coefficient for price is negative at a 1% significance level, reflecting that farmers are cost-sensitive and prefer ADS with lower prices. The positive estimate for supplier localness suggests farmers are more likely to choose a local supplier over a nonlocal one. Concerning service quality guarantees, farmers prefer to sign a contract to reduce the outcome uncertainty, compared to an oral agreement. Moreover, all standard deviations of the parameters are highly significant, as shown in Model (2), indicating farmers' preferences are substantially heterogeneous across these non-fixed attributes at the individual level. To explore the underlying sources of heterogeneity, we extended Model (2) by including interactions between the attributes and a set of individual-specific characteristics.

In Model (3), the interaction terms with ASC sketch the characteristics of farmers who opt out in choice sets. The variables of farmer, household, and farm characteristics include age, education level, risk preference, off-farm labor, cooperative membership, household income, farmland topography, contiguous plot size, drone learning channels, and adoption experience. The interaction between age and ASC is positive and significant, meaning that younger farmers are less likely to opt out and have a higher possibility of adopting ADS. Aligning with existing literature on digital technology adoption, the education of farmers is found to be positively associated with their preferences for ADS. The negative coefficient of household income interacted with ASC indicates that households with higher annual income have a positive attitude toward choosing ADS, although it is not statistically significant. The coefficient of farmland topography interacted with ASC is negative, implying that the worse the farmland topography, the more willing farmers are to hire agricultural drones to perform relevant cropping operations. The parameter of the interaction term between ASC and contiguous plot size is estimated to be negative, but insignificant, reflecting that the size of contiguous plots is not the major constraint in the case of drone services. In terms of drone learning channels, the results illustrate that word-of-mouth learning has a strong correlation with farmers' adoption decisions, while no significant effects are found for other channels. As expected, the coefficient of adoption experience interacted with ASC is negative and statistically significant, suggesting that farmers who have used agricultural drones before are inclined to choose ADS in the choice experiment.

Models (4) and (5) demonstrate the role of farmer characteristics on preference for attributes associated with supplier uncertainty in adoption, i.e., localness of service supplier and form of agreement. In Model (4), age is found to be significantly associated with the localness of suppliers, and its negative coefficient implies that younger farmers have a greater intention to adopt ADS provided by local suppliers. Word-of-mouth regarding agricultural drones has significant positive effects on farmers' preferences for supplier localness. In Model (5), farmers with higher education levels prefer to sign contracts rather than reach oral agreements. In addition, the negative effect of off-farm labor input suggests that households without off-farm labor are highly dependent on agricultural production and need to sign a contract to reduce the adoption uncertainty. Farmers with experience in hiring ADS have a higher propensity to develop oral agreements than contracts, as the adoption experience improves farmers' knowledge and perceived reliability of ADS, thereby raising the probability of choosing oral agreements with higher flexibility.

In general, farmers prefer adopting one of the ADS over no adoption, and a low price, local supplier, and contractual agreement tend to increase the utility of choosing ADS. More specifically, potential adopters in this choice experiment are characterized by youth, higher education, poor-topography farms, word-of-mouth drone learning, and adoption experience. Farmers who are young and learn about agricultural drones through word-of-mouth prefer local suppliers over nonlocal ones. Farmers who choose to sign a contract are highly educated, with full-time farm work and no adoption experience.

4.2. Marginal WTP estimation

Table 4 reports the WTP along with the confidence intervals, which were obtained from the estimates of the basic mixed logit model (Model 2 in Table 3). The WTPs could be interpreted as the maximum technology fee a farmer is willing to pay for the ADS and its attributes (Schwirplies *et al.* 2019). On average, the WTP of ADS is estimated to be 24.896 CNY per mu (approximately 53 USD per ha), meaning the maximum payment for switching the current practice to the ADS is 24.896 CNY per mu, higher than the actual market price. Reasons for the higher WTP include: First, the small farm size of our target sample, smallholders, means the overall cost of the service is still relatively low. Even if the per-unit service price is higher, the cost is still acceptable. Additionally, there are narrow price gaps among ADS alternatives. Farmers rarely opt out due to the higher price during the experiment. This may also lead to a higher WTP for the ADS. Furthermore, as farmers engage in off-farm activities, the opportunity cost for labor is increasing. For

Table 4 Mean marginal willingness to pay (WTP) for agricultural drone services (ADS) and its attributes in the full sample[1)]

Attribute	WTP	5%	95%
ADS	24.896	19.021	33.688
Localness	4.056	3.195	5.295
Agreement	1.396	0.127	2.453

[1)] We apply the Krinsky-Robb method bootstrapped 10,000 times to estimate 95% confidence intervals, where 5% is the lower limit and 95% is the upper limit. WTPs for ADS in Table 4 and Fig. 3 are based on the minus estimate of alternative specific constants (ASC).

these farmers, the efficiency and convenience of adopting drones outweigh the cost, because adopting drones helps them save time for other work. Especially, the WTP is on par with the labour cost of manual spraying, calculated as the average daily wage of local labor divided by the number of mu sprayed per day. It reflects that farmers would adopt ADS as long as the price does not exceed the labor cost. In addition, respondents are willing to pay an additional 4.056 CNY per mu for local suppliers than nonlocal ones, indicating nonlocal service suppliers may need to lower prices to strengthen their competitiveness. Regarding the form of agreement, the price premium for a contract is 1.396 CNY per mu, compared to an oral agreement. The positive WTP indicates that farmers prefer contracts over oral agreements. Moreover, the WTP for supplier localness is higher than that for agreement, implying farmers tend to assign a higher priority to the localness of suppliers than to the form of agreements when making the adoption decision. This evidence is further supported in the following subgroup analysis.

The above WTPs quantify average preferences for ADS across all respondents. However, the significant standard deviations in MXL models indicate that there is a great deal of preference heterogeneity across individuals. To gain a deeper understanding of this regard, we calculate the marginal WTPs by subgroups based on the relevant sociodemographic characteristics to identify the observed heterogeneity and distinguish the priorities for identifiable groups within the full sample.

Fig. 3 summarizes the subgroup WTP measures for ADS, the local supplier, and the contract, respectively. It is noted, in addition to the individual-specific characteristics mentioned previously, that we are also interested in the heterogeneous preferences of rice farmers and farmers from different regions, so we estimate WTPs for these sub-samples. Consistent with the results of overall average WTPs (Table 4), the WTP 95% confidence intervals for ASC and local suppliers both do not include the null value (gray dash lines in Fig. 3), indicating farmers have significant preferences for ADS and local suppliers across all subgroups. In contrast, the WTP estimates of contracts are relatively small and in some subgroups are not even statistically significant. This may be explained in two folds: First, farmers hold divergent preferences for oral and contractual agreements. That is, some prefer the perceived flexibility of oral agreements, while others value the security and clarity offered by formal contracts. This heterogeneity in preferences can lead to high variability in responses, making it difficult to detect significant WTPs. Second, the enforcement of contracts requires

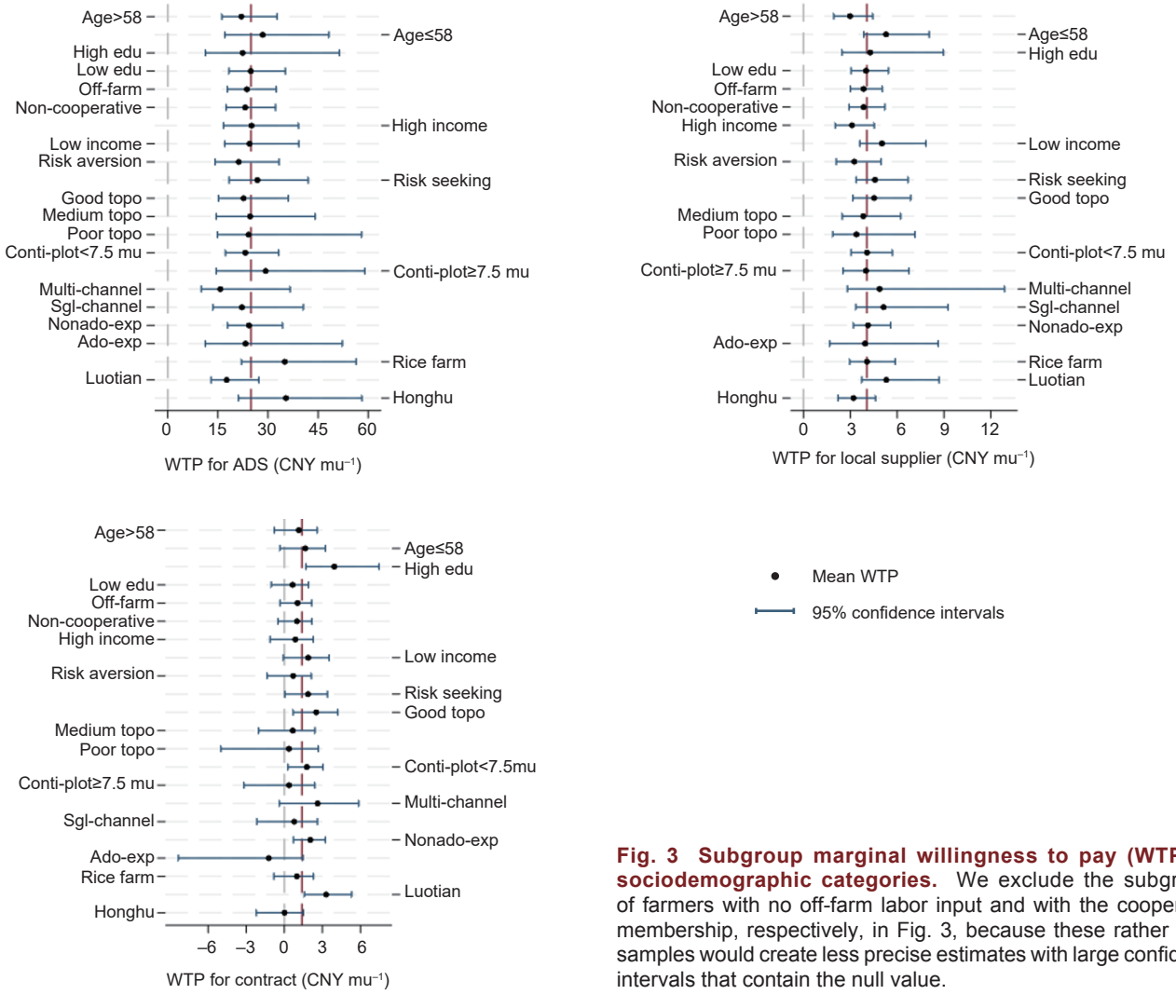


Fig. 3 Subgroup marginal willingness to pay (WTP) by sociodemographic categories. We exclude the subgroups of farmers with no off-farm labor input and with the cooperative membership, respectively, in Fig. 3, because these rather small samples would create less precise estimates with large confidence intervals that contain the null value.

higher transaction costs, especially for disadvantaged farmers, which would lower their WTP for drone services with contracts. Nevertheless, the subgroup WTPs for contracts partly support the results of interaction terms (Table 3, Model 5), indicating farmers with high education and no adoption experience prefer signing contracts.

Subgroup WTPs enable us to match heterogeneous preferences with specific individual characteristics, which would help ADS suppliers categorize potential target consumer groups to offer appropriate services. Benchmarked with the overall average WTPs (red dashed lines in Fig. 3), those attaching higher WTP for ADS have the following salient characteristics: young (age≤58 years), high household income, risk-seeking, the largest contiguous plot larger than 7.5 mu, and rice farming. These farmers are expected to be early adopters in the villages. Concerning WTPs for these two uncertainty attributes, first, farmers who are highly educated, risk-seeking, own a contiguous plot less than 7.5 mu with good topography, and have no adoption experience are more concerned about supplier uncertainty, as indicated by their higher WTPs for both local supplier and contractual agreement. Another type of farmer attaches more importance to local suppliers only, but cares less about the form of agreement. They are distinguished by youth, with learning channels for drones and rice farming.

In terms of regional heterogeneity, the results show that farmers in Luotian hold a more cautious attitude towards agricultural drones. Correspondently, they are willing to pay more for local suppliers and contracts to reduce supplier uncertainty in the adoption process as compared to farmers in Honghu. In our survey, many farmers in Luotian revealed their concerns about the new technology, whether agricultural drones could perform well in fragmented, with-obstacle (like trees, etc.), and irregular arable land. In the mountainous and less developed areas, only 2% of farmers had used drones before. On the contrary, Honghu is more developed and has relatively large arable land per household, and around 33% of farmers in Honghu already have experience in ADS. Therefore, farmers in Honghu feel less uncertain about hiring ADS and are less sensitive to the localness of suppliers and the form of agreement.

5. Discussion

In this study, although there is little adoption experience of agricultural drones among sampled farmers so far, the results of choice models and WTPs consistently identify farmers' positive preferences for ADS. This supports the promise of the adoption mode by hiring outsourced drone services in smallholder farming systems. Following the conceptual framework of Meijer *et al.* (2007), we corroborate that farmers do perceive the uncertainty concerning the supplier localness and the form of agreement; they are more likely to choose the ADS with local suppliers and contracts. This finding partly enriches the empirical evidence that uncertainty could be an inhibiting factor of smallholder innovation adoption (Chavas and Nauges 2020; Wu *et al.* 2023). Additionally, farmers' preferences for local suppliers are found higher than that for contracts, reflecting that the mindset of acquaintanceship is deeply embedded in farmers' decision-making process. Farmers place greater reliance on personal connections and community networks than on formal binds in China (Fang *et al.* 2024). Hence, farmers believe that localized relationship is more valuable than agreements in rural areas. In particular, it is important that farmers can access local ADS suppliers promptly when they have any questions or feedback regarding the usage of agricultural drones.

The analysis of preference heterogeneity uncovers the relationship between individual-specific characteristics and ADS preferences. Firstly, our analysis confirms that age plays an important role in agricultural drone adoption (Michels *et al.* 2020), although some studies found no significant effect in this regard (Zheng *et al.* 2019; Wachenheim *et al.* 2021). More interestingly, we find that younger farmers are more willing to hire ADS and have a stronger tendency to choose local suppliers. Younger farmers, who are more likely to be engaged in off-farm work or other potential earnings, would have higher labor opportunity costs to perform manual agricultural tasks. Adopting drone services for spraying or monitoring could help them save time for other activities. For the choice of supplier localness, young farmers are more sensitive to localness uncertainty, while elderly farmers, with higher social capital and more farming experience, have more confidence in handling the uncertainty in the transaction process.

Farm size has been considered another important factor in driving technology adoption. Existing studies assert that farm size would be a barrier for smallholders to adopt high-cost digital technologies due to diseconomies of scale, which may lead to a digital divide between large and small farms (Cochran *et al.* 2004; Ding *et al.* 2022; Khanna *et al.* 2022). In the case of ADS, we find that uptake intention is not significantly constrained by the scale of the contiguous plot. On the one hand, this supports Igata *et al.* (2008), who claimed that agricultural technology services could be helpful to mitigate scale dependence and lower investment costs by outsourcing the operation of emerging technology to specialists, thus motivating the willingness of farmers with different farm sizes. More importantly, we highlight that the collective usage of external services can be a promising means of linking smallholder farmers to advanced technologies, without the expansion of farm size. Drones fly over plots that are contiguous and have the same crop.

In addition, we estimate the correlation between learning channels and farmer adoption intention. The results show that word-of-mouth learning positively correlates with the preferences for ADS and supplier localness, whereas traditional and digital media have no effect on preferences for ADS and its attributes. Interpretations can be presented: First, it implies that word-of-mouth still plays an important role in innovation dissemination in rural areas, despite farmers having access to traditional and digital media currently. This finding contributes to the debate on the effect of learning channels on agricultural technology adoption (Maertens 2017; Yue *et al.* 2023). Second, farmers who used to exchange drone knowledge with acquaintances are more willing to adopt ADS from the same county. This might be because information on the new technology obtained through

social interaction tends to be limited and homogenous, which may lead to incomplete technology cognition and more dependence on local suppliers with lower perceived uncertainty. This parallels the findings of Li *et al.* (2023).

Finally, this study provides weak evidence on the relationship between risk preference and adoption decision, where we find no significant difference in ADS preferences between the risk-averse and risk-seekers. This validates the research by Marra *et al.* (2003), who argue that adopting new technology might increase risk in the short term but probably reduce risk in the long term. For example, drones can be used for pest control and decrease the risk of crop damage, although in the beginning, farmers may feel uncertainty about the service quality. Farmers may weigh these two risk dimensions differently, thus leading to an insignificant result in this context (Pedroni *et al.* 2017). In addition, risk preference is not assumed to be exogenous in this model. Farmers' risk preferences may themselves be influenced by peer effects within social networks, prior exposure to innovation, and structural factors such as weather and training. These dynamics may confound the estimates, resulting in the observed insignificance. Therefore, we suggest that further research may benefit from using instrumental variables or panel data to better address this issue. Moreover, the lottery game used in our survey measured farmers' general risk preferences, while it is noted that risk preferences are sensitive to the elicitation methods and the context (Finger *et al.* 2023). Therefore, more research should be encouraged to check the stability of the result by using measurements specific to the innovation.

Limitations of this study need to be acknowledged to guide future research on ADS. First, our findings stress the importance of dissemination channels in technology adoption but the specific effect of digital media is not identified. With the penetration of the internet and the use of ICTs, more and more farmers have access to digital media to obtain extensive information related to agricultural innovation (Ward *et al.* 2018; Mohammed and Abdulai 2022). Future research could follow the work and further explore the role of digital media, like WeChat official accounts and TikTok videos, in farmers' technology adoption.

Second, the focus of this paper is on supplier uncertainty in adoption. Considering the cognitive burden of large choice cards in the smallholder context and dominant options, we decided on a concise experimental structure. With the diffusion and application of agricultural drones, farmers' knowledge and cognition of the technology will increase in the case region. In this light, future design could be extended to include more factors of ADS to simulate growing trade-offs in reality, such as the reputation of service suppliers, historical performance, technological expertise, drone's functionality, and compatibility with crops.

Third, we base experimental scenarios on the premise that farmers are generally able to collectively hire ADS to relieve the scale constraint in reality. However, various collective action problems can result in high transaction costs hindering the hiring of drone services. As controlling for these transaction costs was beyond the scope of this study, we implicitly assumed that collective actions are fairly homogenous across our sample and not an absolute exclusion criterion for hiring drone services. On the one hand, the lack of incorporating transaction costs may increase the hypothetical gap between expressed intention to adopt and actual adoption. Meanwhile, we also have to consider that hiring manual labor, the dominant choice under non-adoption of drone services due to the old age of many farmers, may in reality be connected to considerable transaction costs as well. In the past few years, rural-urban labour migration has resulted in an increasing scarcity of hired farm labour, especially during peak times. This aspect may again contribute to closing the hypothetical bias of stated preferences in our choice experiment. Overall, the assumption of homogeneity of transaction costs across households may seem crude at first glance, while we have to consider the strong homogeneity of most smallholder family farmers in our sample. Nevertheless, future research could focus on the underlying heterogeneous effects of collective actions and discuss them with mechanisms of peer pressure or free-riding, thus guiding the design of organizational institutions.

Last but not least, we have to admit the underlying existence of hypothetical bias in our study (Penn and Hu 2018). Because we simulated the decision-making process rather than observed the actual adoption behavior, farmers may overstate their WTP in the hypothetical scenarios. Therefore, more choice experiments are suggested to be implemented with actual service supplies and adoption in different circumstances of other regions to validate and generalize the results.

6. Conclusion and implications

With a digital transformation in agriculture, drones are expected to be one of the promising technologies to address the challenges of inefficient labor input, overuse of agrochemicals, and inaccurate crop monitoring, and contribute to environmental sustainability. However, smallholder farmers most often lag behind in exploiting the benefits of such advanced technologies. Besides high investment costs, the complexity of technical operation and maintenance is also a major barrier for most farmers. Agricultural drone services outsourced by professional teams can overcome these difficulties but also introduce more uncertainty, especially in terms of suppliers. Therefore, it warrants pondering smallholder farmers' preferences for ADS and the role of supplier uncertainty in the process.

Using a discrete choice experiment, the study investigates farmers' preferences for agricultural drone services in smallholder farming systems in Hubei, China. The results show that 1) farmers in the study area are willing to adopt agricultural drones as a service on the premise of collective hiring. To further explore the role of supplier uncertainty in farmers' adoption decisions, we take into account the localness of suppliers and the form of agreements as ADS attributes and find ADS with local suppliers and contractual agreements are preferred by farmers due to their lower uncertainty. 2) Substantial heterogeneity in preferences for ADS and its attributes is identified and could be explained by individual-specific characteristics. Specifically, farmers

with youth, higher education, owning poor-topography farms, drone learning *via* word-of-mouth, and adoption experience are more likely to hire ADS than farmers who do not display these characteristics. Farmers who are young and learn about agricultural drones through word-of-mouth prefer local suppliers over nonlocal ones. Farmers who choose to sign a contract tend to be highly educated, with full-time farm work, and no adoption experience. 3) The willingness to pay analysis indicates that farmers are willing to pay 25 CNY per mu (53 USD per ha) on average for ADS. Notably, farmers value the localness of suppliers more than the form of agreements when choosing a particular drone service.

Based on these results, we draw some practical recommendations for the adoption of ADS. First, more efforts should be made to educate farmers about the information regarding drones as an emerging agricultural technology. Our study finds that farmers currently receive very limited and homogenous information about agricultural drones mainly through word-of-mouth. This leads them to rely heavily on these attributes with high credence, such as local services and contracts. In this respect, multiple and diverse ag extensions are necessary to raise farmers' awareness of agricultural drone technology, especially its reliability. To be specific, more field demonstrations could be organized so that farmers could see drone applications in real time. Digital media, like WeChat groups and TikTok, could be used to share drone-related information with farmers. In the long term, the government plays an important role in regulating the drone industry, motivating the development of ADS teams, and eventually enhancing farmer adoption. In particular, with the diffusion of such outsourced ADS, the relevant authorities ought to consider issues including: first, improving the training of professional pilots to ensure service quality and safety; second, monitoring agreements regarding service scope, price structures, and liability clauses; third, subsidizing the adoption insurance to reduce risks for early adopters. Our evidence on heterogeneous preferences may help speed up ADS promotion. For instance, it is more effective for service suppliers to target farmers with high human capital and poor resource endowment, as they express higher adoption intention. For nonlocal service teams, forming joint service branches with local cooperatives could increase credibility and accelerate diffusion in regions where trust in external services is low. There are multiple successful cases where local cooperatives play a crucial role in organizing and coordinating farmers to collectively hire drone services (MARA 2021). This deserves to be publicized and replicated by the relevant authorities. This research may also offer insights into the adoption of additional digitalization technologies among smallholders in China and numerous other developing countries characterized by smallholder farming.

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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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