frontiers in Sustainable Food Systems

TYPE Original Research
PUBLISHED 16 March 2026
DOI 10.3389/fsufs.2026.1755351

OPEN ACCESS

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RECEIVED 27 November 2025
REVISED 30 January 2026
ACCEPTED 02 February 2026
PUBLISHED 16 March 2026

CITATION
Zheng P and Wang H (2026) Social media and drone adoption in mountainous fruit production: the mediating role of technology cognition. *Front. Sustain. Food Syst.* 10:1755351. doi: 10.3389/fsufs.2026.1755351

Social media and drone adoption in mountainous fruit production: the mediating role of technology cognition

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Social media platforms have been reshaping the dissemination of agricultural technology information, yet the mechanisms through which these platforms influence advanced machinery adoption among smallholder farmers in mountainous regions remain insufficiently understood. Based on the Technology Acceptance Model (TAM), this study constructed an analytical framework of "social media use → technology cognition → adoption behavior" and introduced terrain conditions as a contextual moderating variable. We collected survey data from 650 mountainous fruit farmers across Shaanxi, Yunnan, and Hunan provinces in China, and employed Logistic regression models, Bootstrap mediation tests, and instrumental variable methods to systematically examine the effects of social media use on plant protection drone adoption decisions. The results demonstrate that social media use intensity exerts a significant positive effect on drone adoption (OR = 2.68, $p < 0.001$), with users showing a 34 percentage point higher adoption probability than non-users. Mechanism analysis reveals that technology cognition—combining perceived usefulness and perceived ease of use—partially mediates the relationship between social media and adoption behavior, accounting for 40.8% of the total effect (95% CI: 0.28–0.54). Heterogeneity analysis indicates that terrain conditions significantly moderate this relationship: the marginal effect of social media among mountainous farmers is 2.74 times that of plain farmers (OR = 4.14 vs. OR = 1.51). Regional analysis reveals social media effects range from OR = 1.93 (Hunan) to OR = 3.77 (Shaanxi), supporting the terrain moderation mechanism. This study extends TAM in mountainous agricultural contexts and identifying terrain as a critical moderator, providing empirical evidence for optimizing digital agricultural extension strategies and bridging the technology adoption gap in mountainous areas.

KEYWORDS
mediation effect, moderation effect, mountainous agriculture, plant protection drone, social media, technology acceptance model, technology adoption

1 Introduction

With a significant standing in agricultural production, mountainous fruit cultivation greatly faces severe challenges in the plant protection area. In general, large-scale machinery is still very hard to use on steep slopes and fragmented land parcels in mountainous areas. Due to its inefficiency and intensive labor, traditional manual backpack spraying operation significantly raises pesticide exposure risks, posing serious threats to farmers' health. Since the agricultural labor force of China has continuously been aging and out migrating, the average age of agricultural workers now exceeds 50 years, and rural hollowing-out has become increasingly prominent. These demographic shifts have severely challenged the sustainability of traditional plant protection methods. Plant protection drones, an emerging precision agriculture technology, have rapidly been developed in recent years as an alternative in such scenarios to tackle the challenges of mountainous fruit tree protection.

As a critical innovation in precision agriculture, plant protection drones offer promising solutions for mountainous orchard management. China's plant protection drone industry has seen remarkable growth. The national fleet reached 251,000 units by 2024, covering an operational area of 178 million hectares, up about 25% compared to 2023 (China Daily, 2025). Some studies have shown that drone-based plant protection can bring in an additional income of 434–488 USD per hectare for farmers and greatly reduce operation time (Quan et al., 2023). Despite these apparent advantages of the technology, the adoption rate among mountainous fruit farmers is still low, and the factors and mechanisms that determine the process need to be further explored. According to innovation diffusion theory, technology adoption is a kind of process transmitted through social networks (Rogers et al., 2014). Both social networks and extension services affect farmers' efficiency in adopting technologies (Wang et al., 2020). Social interaction influences farmers' decisions to adopt technology through several mechanisms: endogenous interaction (herding effects), contextual interaction (demonstration effects), and social norms (Wang and Xu, 2024).

The rapid proliferation of social media in rural China has opened up new channels for disseminating agricultural technology. In 2023, about 27.78 million videos on agricultural technology were published through Douyin and gained 120.6 billion views. There were 216,000 agricultural technology creators on the Kuaishou platform, with more than 50,000 h of live streaming every day, covering 26,800 townships across the country (People's Daily Online, 2024). The way that farmers obtain technological information is being reshaped by the features of short videos, including intuitiveness, fragmentation, and interactivity. However, how social media influences farmers' technology adoption behavior remains an open question. It has been reported that farmers' participation in social media can significantly improve their willingness to adopt low-carbon agricultural technologies (Yang et al., 2021). Digital multimedia has also been shown to facilitate green production technology adoption through perceived usefulness and perceived ease of use (Yu et al., 2024).

There are several limitations in the current literature. For research subjects, existing studies predominantly have focused on drone adoption for grain crops in plain regions, while paying little attention to fruit cultivation in mountainous and hilly areas. Mountainous orchards face distinct challenges—steeper slopes (15–35°), fragmented land parcels, and higher manual labor intensity—making traditional plant protection both dangerous and inefficient, yet these contexts remain understudied (Quan et al., 2023). For influencing factors, most studies have emphasized the role of external variables such as farmers' resource endowments and social networks, while relatively few studies have explored the role of social media (Zheng et al., 2021). As for the mechanisms, existing research has primarily employed direct effect analysis, without exploring the psychological mechanisms through which social media influences technology adoption. According the TAM, perceived usefulness and perceived ease of use are core psychological variables affecting technology adoption (Davis, 1989). However, whether social media can promote adoption by changing these technology cognitions remains unverified empirically. While TAM has been extensively tested in organizational settings and increasingly applied to agriculture, its applicability among resource-constrained smallholders in mountainous contexts requires validation. Whether mountainous terrain, as an important contextual factor, moderates the effects of social media remains unexplored, despite theoretical reasons to expect stronger effects in information-constrained areas.

Based on these research gaps, this study chose to conduct its research in the following areas: apple production areas in Yan'an, Shaanxi Province; banana and mango production areas in Yunnan Province; and citrus production areas in Hunan Province. In total, data from 650 mountainous fruit farmers were collected through household surveys to systematically analyze the effects of social media use on the adoption of plant protection drones, reveal the mediating role of technology cognition, and explore the moderating effects of terrain complexity. Three core questions are answered in this research: Does the use of social media promote the adoption of a plant protection drone by mountainous fruit farmers? Does technology cognition play a mediating role between them? Does terrain complexity moderate the effects of social media? Our theoretical contribution lies in extending TAM to mountainous agricultural contexts, validating that perceived usefulness and ease of use mediate social media's effect, and identifying terrain complexity as a critical boundary condition for digital extension effectiveness. The findings will provide empirical evidence for the digital transformation of mountainous agriculture, thus responding to the strategic deployment of "low-altitude economy empowering rural revitalization" proposed in the Central Committee of the Communist Party of China and State Council, 2025.

2 Materials and methods

2.1 Study area and sampling

This study selected three representative mountainous fruit production regions in China for field investigation (as shown in Figure 1): Yan'an City in Shaanxi Province (apple cultivation, Loess Plateau mountainous terrain, elevation 800–1,200 m, slope 15–25°), Yuxi City and Dehong Prefecture in Yunnan Province (banana and mango cultivation, alpine valley terrain, elevation 600–1800 m, slope 20–35°), and Huaihua City and Yongzhou City in Hunan Province (citrus cultivation, hilly terrain, elevation 200–600 m, slope 5–15°). These three regions encompass the major types of mountainous fruit trees and terrain gradients in China, providing good representativeness.

A stratified random sampling method was employed. The sampling frame was first stratified according to terrain type (plain/hilly/mountainous) and drone adoption status (adopted/not adopted), and then farmers were randomly selected within each stratum. During September–November 2024, data were collected through household interviews. A total of 650 valid questionnaires were completed, including 300 mountainous samples, 220 hilly samples, and 130 plain samples. Data quality control included logical consistency checks and outlier elimination, achieving a valid questionnaire rate of 94%. Informed consent was obtained from all surveyed farmers, and this study was approved by the Ethics Committee of Hebei Agricultural University.

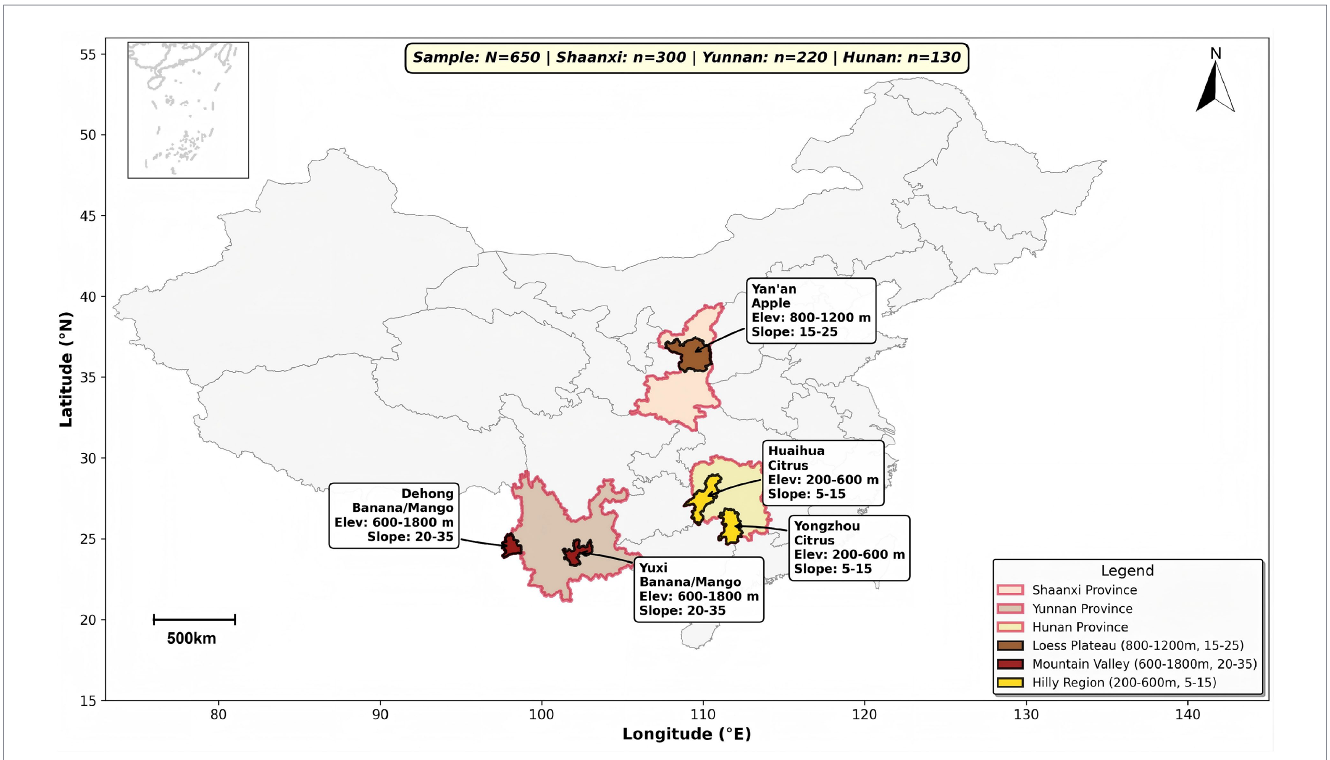

FIGURE 1
Study area and geographical distribution.

TABLE 1 Variable definitions and descriptive statistics.

Variable	Definition	Mean	SD	Min	Max
Dependent variable					
Drone Adoption	1 = adopted, 0 = not adopted	0.426	0.495	0	1
Independent variable					
Social Media Use	Standardized composite index	0.000	1.000	−1.52	2.38
Mediator					
Technology Cognition	Average score of 6 items (1–5)	3.51	0.78	1.50	5.00
Perceived Usefulness	Average of 3 items (1–5)	3.86	0.85	1.00	5.00
Perceived Ease of Use	Average of 3 items (1–5)	3.16	0.92	1.00	5.00
Moderator					
Terrain Type	1 = plain, 2 = hill, 3 = mountain	2.26	0.77	1	3
Slope Degree	Average slope (degrees)	12.8	7.2	1.5	28.0
Control variables					
Age	Years	48.3	10.5	25	68
Education	Years of schooling	8.6	2.8	6	15
Household Income	Annual income (10,000 CNY)	8.2	5.4	1.5	28.0
Orchard Size	Orchard area (mu*)	12.4	8.2	2.0	50.0

1 mu = 0.067 hectares. *N* = 650. For detailed questionnaire items and coding procedures (see Supplementary Appendices A, B).

2.2 Variable measurement

The main variables involved in this study and their measurement methods are presented in Table 1.

The dependent variable was plant protection drone adoption (Drone Adoption), measured by asking farmers "Does your household currently use drones for fruit tree pesticide application?" Users were coded as 1, and non-users were coded as 0.

The independent variable was social media use intensity (Social Media Use), measured using a three-dimensional comprehensive approach: number of platforms used (Douyin, Kuaishou, WeChat, Toutiao, ranging from 0 to 4), daily usage duration (5-point Likert scale: 1 = never, 2 = less than 30 min, 3 = 30–60 min, 4 = 1–2 h, 5 = more than 2 h), and frequency of agricultural technology information acquisition (5-point Likert scale: 1 = never, 2 = rarely, 3 = sometimes, 4 = often, 5 = daily). To construct the composite index, each indicator was first standardized using z-scores, then weighted based on exploratory factor analysis results. Specifically, platform number received a weight of 0.3 (factor loading = 0.76), usage duration received 0.3 (loading = 0.74), and information frequency received 0.4 (loading = 0.82). The composite index explained 68.3% of total variance (KMO = 0.71, Bartlett's test $p < 0.001$), indicating adequate construct validity (see Supplementary Appendix C for full EFA results).

The mediating variable was technology cognition (Technology Cognition). We conceptualize it as farmers' overall cognitive evaluation of drone technology, combining perceived usefulness and ease of use. This approach is justified by: (1) farmers' qualitative responses showed conflation of the two concepts, and (2) high inter-construct correlation ($r = 0.68$, $p < 0.001$). Based on the Technology Acceptance Model (TAM) (Davis, 1989), we designed a six-item scale comprising perceived usefulness (3 items: "Drones save time compared to manual spraying," "Drones improve pesticide application effectiveness," "Drones reduce my health risks from pesticide exposure") and perceived ease of use (3 items: "Learning to operate drones is easy for me," "Drone operation does not require advanced technical knowledge," "Technical problems with drones can be easily solved") (see Supplementary Appendix A for complete questionnaire) A 5-point Likert scale was employed (1 = strongly disagree, 5 = strongly agree). The average score of the six items served as the composite score. The scale demonstrated good reliability with a Cronbach's α coefficient of 0.87, with item-total correlations ranging from 0.62 to 0.78 (see Supplementary Appendix D for detailed scale validation).

The moderating variable was terrain type (Terrain Type). Based on the actual terrain of farmers' orchards, terrain was classified into three categories: plain (flat or gentle slope), hilly (small slope), and mountainous (steep slope), coded as 1, 2, and 3, respectively. The average orchard slope (°) was also recorded for robustness checks.

Control variables included: age (continuous variable, years), education years (primary school and below = 6 years, junior high school = 9 years, senior high school/technical secondary school = 12 years, college and above = 15 years), annual household income (converted to continuous variable using interval midpoint, 10,000 yuan), and orchard size (continuous variable, mu). Descriptive statistics for all variables are presented in Table 1.

2.3 Analytical strategy

A progressive analytical strategy was adopted in this study to examine the mechanisms through which social media use influences plant protection drone adoption. The conceptual framework is illustrated in Figure 2. The baseline model employed binary Logit regression to test the main effect of social media on adoption. The model is specified as:

$$P(\text{Adoption}=1)=\frac{\exp(\beta_0+\beta_1\text{SocialMedia}+\beta_2\text{Controls})}{1+\exp(\beta_0+\beta_1\text{SocialMedia}+\beta_2\text{Controls})} \quad (1)$$

where β_1 represents the main effect coefficient of social media use, and Controls denotes the vector of control variables.

Mediation effects were tested using the Bootstrap method (5,000 replications) to examine the mediating role of technology cognition

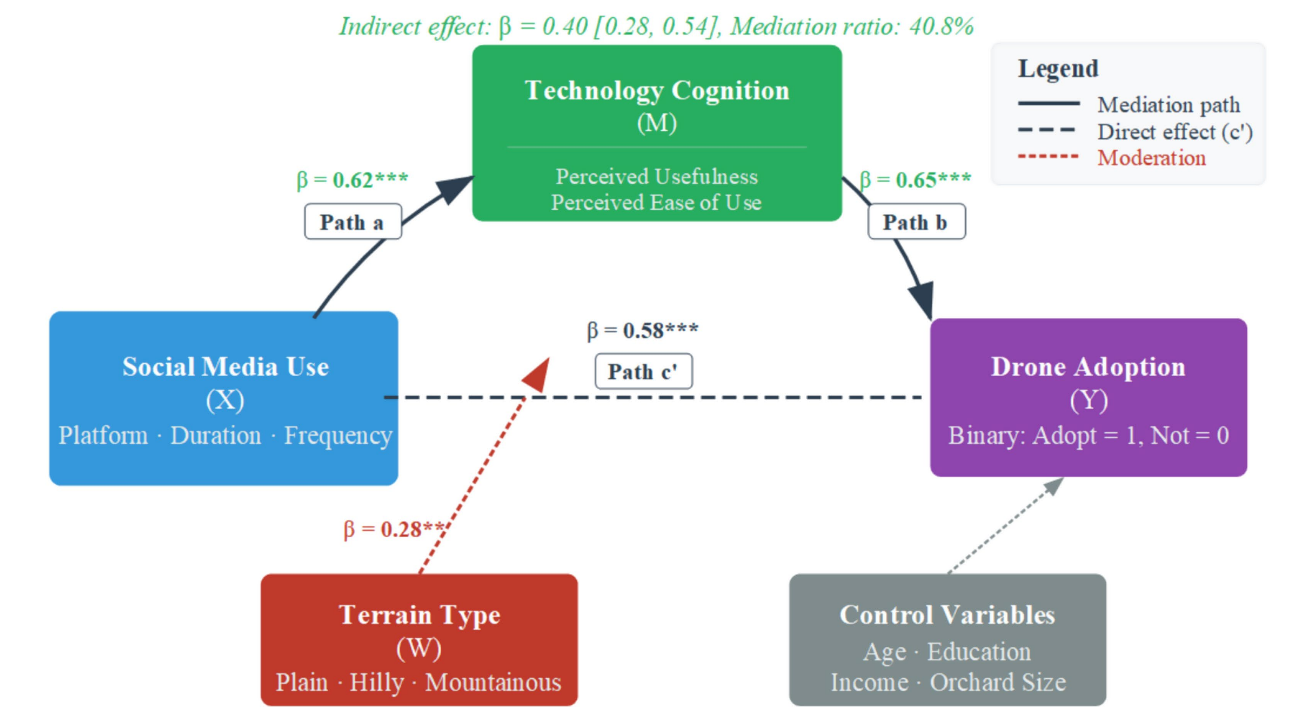

FIGURE 2
Conceptual framework.

(Bolin, 2014; Preacher and Hayes, 2008), following a three-step procedure. Step 1 tested the total effect of social media on adoption (path *c*):

$$\text{Adoption} = c \cdot \text{SocialMedia} + \gamma \cdot \text{Controls} + \varepsilon_1 \tag{2}$$

Step 2 tested the effect of social media on technology cognition (path a):

$$\text{TechCognition} = a \cdot \text{SocialMedia} + \delta \cdot \text{Controls} + \varepsilon_2 \tag{3}$$

Step 3 simultaneously incorporated social media and technology cognition to test their effects on adoption, yielding the direct effect (c') and the effect of technology cognition (path b):

$$\text{Adoption} = c' \cdot \text{SocialMedia} + b \cdot \text{TechCognition} + \theta \cdot \text{Controls} + \varepsilon_3 \tag{4}$$

The indirect effect was calculated as $a \times b$, and the proportion of mediation effect was computed as $(a \times b)/c$. If the Bootstrap 95% confidence interval does not contain 0, the mediation effect is considered significant.

Moderation effects were tested by constructing interaction terms to examine the moderating role of terrain complexity. The model is specified as:

$$\begin{aligned}\text{Adoption} &= \beta_0 + \beta_1 \text{SocialMedia} + \beta_2 \text{Terrain} \\ &+ \beta_3 (\text{SocialMedia} \times \text{Terrain}) + \beta_4 \text{Controls} + \varepsilon\end{aligned} \tag{5}$$

If the interaction term coefficient β_3 is significant, the moderation effect is established. Further group regression by terrain type and simple slope tests were conducted to verify differences in social media effects across different terrain conditions.

Regarding endogeneity concerns, a dual strategy combining instrumental variable two-stage least squares (IV-2SLS) (Wooldridge, 2010) and propensity score matching (PSM) (Rosenbaum and Rubin, 1983; Caliendo and Kopeinig, 2008) was employed. The selection of instrumental variables in this study drew upon practices from research on agricultural technology adoption efficiency (Wang et al., 2020), ensuring both exogeneity and relevance of the instrumental variables. For the IV approach, county-level internet penetration rate in 2010 (IV) was used as the instrumental variable. The first-stage regression is:

$$\text{SocialMedia} = \alpha_0 + \alpha_1 \cdot \text{IV} + \alpha_2 \cdot \text{Controls} + \mu \tag{6}$$

The second stage substituted the predicted value Social media into the adoption equation:

$$\text{Adoption} = \beta_0 + \beta_1 \cdot \text{SocialMedia} + \beta_2 \cdot \text{Controls} + \nu \tag{7}$$

The first-stage F statistic is required to exceed 10 to ensure instrument strength (Stock and Yogo, 2005). For PSM, 1:1 nearest neighbor matching was employed, and the average treatment effect on the treated (ATT) was calculated as:

$$\text{ATT} = \frac{1}{N_T} \sum_{i \in T} \left(Y_i - \sum_{j \in C} w_{ij} Y_j \right) \tag{8}$$

where N_T denotes the sample size of the treatment group, and w_{ij} represents the matching weight. The matched sample is required to pass the balance test (standardized bias < 5%).

Robustness checks included: (1) replacing the dependent variable by substituting actual adoption with adoption intention (1–5 scale), estimated using the Ordered Probit model (Greene, 2018).

3 Results

3.1 Descriptive analysis

The basic characteristics and drone adoption status across different terrain types are presented in Table 2. Overall, the 650 sampled farm households had a mean age of 48.3 years, 8.6 years of education, an annual household income of 82,000 yuan, and an orchard size of 12.4 mu. The overall drone adoption rate was 42.6%; however, significant differences were observed across terrain types ($\chi^2 = 68.5$, $p < 0.001$): the adoption rate was highest in mountainous areas (57.3%), followed by hilly areas (38.2%), and lowest in plain areas (20.8%), exhibiting a distinct terrain gradient pattern.

As shown in Table 2, comparison across terrain types revealed that mountainous farmers demonstrated higher activity levels in social media use: the platform usage rate reached 78%, noticeably higher than those in hilly (72%) and plain (65%) regions. Technology cognition scores among mountainous fruit farmers (3.68) were also significantly higher than those of hilly (3.48) and plain (3.28) farmers ($F = 7.2$, $p < 0.001$). Notably, although mountainous orchards were relatively smaller in scale (10.8 mu), the adoption rate was paradoxically the highest, which is closely related to the comparative advantages of drones under terrain constraints. Regarding age structure, mountainous farmers were relatively younger (47.1 years) compared to plain farmers (50.2 years), with the difference being statistically significant ($F = 4.8$, $p < 0.01$).

Comparative analysis between adopters and non-adopters indicated that adopters significantly outperformed non-adopters across multiple dimensions: they were 5.4 years younger (44.8 vs. 51.2 years), had 1.4 more years of education (9.4 vs. 8.0 years), earned 27,000 yuan more in household income (98,000 vs. 71,000 yuan), and operated 4.2 mu larger orchards (14.8 vs. 10.6 mu). All differences were significant at the 0.001 level. More importantly, adopters exhibited substantially higher social media use intensity (2.1 vs. 0.98 platforms) and technology cognition scores (4.17 vs. 3.01) than non-adopters, providing preliminary evidence for subsequent mechanism analysis. These patterns are consistent with expectations and provide preliminary evidence for subsequent mechanism analysis.

These descriptive patterns align with theoretical expectations from TAM. Younger farmers and those with higher education showed higher adoption rates, consistent with prior research suggesting these groups have lower perceived complexity and higher technology

TABLE 2 Sample characteristics by terrain type.

Variable	Plain (n = 130)	Hilly (n = 220)	Mountainous (n = 300)	F/χ^2	p-value
Adoption rate					
Drone adoption (%)	20.8	38.2	57.3	68.5	<0.001***
Demographics					
Age (years)	50.2 (10.8)	48.8 (10.4)	47.1 (10.2)	4.8	0.008**
Education (years)	8.2 (2.9)	8.5 (2.8)	8.9 (2.7)	2.1	0.124
Household income (10,000 CNY)	7.8 (5.2)	8.0 (5.3)	8.6 (5.6)	1.8	0.167
Orchard size (mu)	15.2 (9.1)	12.8 (8.0)	10.8 (7.5)	8.5	<0.001***
Social media use					
Platform usage rate (%)	65.0	72.0	78.0	9.2	0.010**
Average platforms (number)	1.25 (1.08)	1.42 (1.15)	1.58 (1.22)	3.2	0.042*
Daily usage time (score)	2.18 (1.32)	2.38 (1.41)	2.62 (1.48)	4.5	0.012*
Technology cognition					
Overall score (1–5)	3.28 (0.82)	3.48 (0.78)	3.68 (0.75)	7.2	0.001***
Perceived usefulness	3.62 (0.89)	3.82 (0.85)	4.02 (0.82)	6.8	0.001***
Perceived ease of use	2.95 (0.95)	3.14 (0.92)	3.32 (0.88)	5.4	0.005**
Terrain characteristics					
Average slope (degrees)	3.2 (2.1)	9.8 (3.5)	18.5 (5.2)	425.8	<0.001***

Standard deviations in parentheses. *, **, *** indicate significance at 10, 5, and 1% levels, respectively.

self-efficacy. Higher-income farmers' greater adoption rates likely reflect stronger perceived usefulness, as they can better capitalize on efficiency gains and risk reduction. The positive association between social media use and both technology cognition scores (r = 0.58, $p < 0.001$) and adoption rates provides preliminary support for our mediation hypothesis, suggesting that social media shapes farmers' perceptions of drone technology.

3.2 Baseline regression results

Before regression analysis, we examined multicollinearity among independent variables. Variance Inflation Factors (VIF) for all predictors were below 2.5 (mean VIF = 1.8), well below the conventional threshold of 10, indicating no serious collinearity concerns. Correlation coefficients among control variables ranged from −0.28 to 0.42, suggesting acceptable levels of independence.

The Logit regression results (Equation 1) examining the effects of social media use on plant protection drone adoption are reported in Table 3. Model 1 included only social media use as the independent variable; the results indicated a significant positive effect on adoption (OR = 2.84, $p < 0.001$), suggesting that the probability of drone adoption among social media users was 2.84 times that of non-users. In Model 2, after controlling for demographic characteristics and farmers' resource endowments, the effect of social media slightly decreased but remained highly significant (OR = 2.68, $p < 0.001$), demonstrating the robustness of the main effect. Model 3 further incorporated terrain dummy variables, and the effect of social media remained stable (OR = 2.71, $p < 0.001$).

As Table 3 shows, the effects of control variables were consistent with theoretical expectations and prior research. Age exerted a negative effect on adoption (OR = 0.96, $p < 0.01$), indicating that each one-year increase in age was associated with a 4% decrease in adoption probability, reflecting older farmers' higher perceived complexity or lower technology self-efficacy. Education years demonstrated a significant positive effect (OR = 1.18, $p < 0.001$); each additional year of education was associated with an 18% increase in adoption probability, indicating that formal schooling enhances farmers' ability to understand and evaluate new technologies. The positive effect of household income was significant at the 5% level (OR = 1.12, $p < 0.05$), reflecting both the importance of economic capacity for technology adoption and potentially higher perceived returns. Orchard size also exhibited a positive effect (OR = 1.05, $p < 0.01$); each additional mu was associated with a 5% increase in adoption probability, suggesting economies of scale in technology adoption. Regarding terrain variables, with plain as the reference group, the OR value for hilly areas was 2.38 ($p < 0.001$), and for mountainous areas it reached 5.24 ($p < 0.001$), indicating that terrain complexity significantly increased the likelihood of drone adoption. This pattern suggests that terrain constraints create rigid demand for labor-saving technologies.

Marginal effect analysis further revealed the substantive impact of social media. Based on Model 3 calculations, when other variables were held at their mean values, an increase in social media use from the lowest level (10th percentile) to the highest level (90th percentile) raised the predicted probability of drone adoption from 22 to 56%, an increase of 34 percentage points. This result demonstrates the substantial practical value of social media in promoting agricultural technology diffusion. Model 3 yielded a pseudo R^2 of 0.385 and a Log-likelihood of −352.8, indicating good overall model fit.

3.3 Mediation effect analysis

To examine the mediating role of technology cognition between social media use and drone adoption, the Bootstrap method (5,000 replications) was employed for three-step analysis, with results presented based on the framework in Figure 2. Step 1 (Equation 2) tested

TABLE 3 Logit regression results for drone adoption.

Variable	Model 1 OR (SE)	Model 2 OR (SE)	Model 3 OR (SE)
Independent variable			
Social media use	2.84***	2.68***	2.71***
	(0.28)	(0.26)	(0.27)
Control variables			
Age (years)		0.96**	0.96**
		(0.01)	(0.01)
Education (years)		1.18***	1.17***
		(0.04)	(0.04)
Household income (10,000 CNY)		1.12*	1.12*
		(0.06)	(0.06)
Orchard size (mu)		1.05**	1.04**
		(0.02)	(0.02)
Terrain type (ref: plain)			
Hilly			2.38***
			(0.42)
Mountainous			5.24***
			(0.89)
Model fit			
Pseudo R^2	0.178	0.325	0.385
Log-likelihood	−487.2	−399.8	−352.8
N	650	650	650
Marginal effects at mean			
Social media (low→high)	+32 pp	+33 pp	+34 pp

Odds ratios (OR) reported. Standard errors in parentheses. *, **, *** indicate significance at 10, 5, and 1% levels, respectively. pp, percentage points.

the total effect; the results showed that social media exerted a significant positive effect on adoption ($\beta = 0.98$, $p < 0.001$), establishing the foundation for mediation effect testing. Step 2 (Equation 3) tested the effect of social media on technology cognition (path a); the regression results indicated that social media use significantly enhanced farmers' technology cognition levels ($\beta = 0.62$, $p < 0.001$), meaning that each one standard deviation increase in social media use intensity was associated with a 0.62 standard deviation increase in technology cognition scores. Step 3 (Equation 4) simultaneously incorporated social media and technology cognition; the results showed that technology cognition exerted a significant positive effect on adoption ($\beta = 0.65$, $p < 0.001$, path b), while the direct effect of social media decreased to $\beta = 0.58$ ($p < 0.001$) but remained significant.

As illustrated in Figure 3, the indirect effect was calculated through the product of path a and path b (a × b = 0.62 × 0.65 = 0.40). Bootstrap confidence interval analysis indicated that the 95% confidence interval for the indirect effect was [0.28, 0.54], excluding zero, confirming that the mediation effect of technology cognition was statistically significant (see Supplementary Appendix E for detailed three-step mediation analysis) The proportion of mediation effect was calculated as (a × b)/c = 0.40/0.98 = 40.8%, indicating that over 40% of the total effect of social media on adoption operated through the psychological mechanism of technology cognition. This result validates the applicability of the Technology Acceptance Model (TAM) in the agricultural technology adoption context, demonstrating that social media promotes adoption behavior by enhancing farmers' perceived usefulness and perceived ease of use regarding drone technology.

Further decomposition of the two dimensions of technology cognition revealed that both perceived usefulness ($\beta = 0.38$, 95% CI [0.26, 0.51]) and perceived ease of use ($\beta = 0.24$, 95% CI [0.15, 0.34]) exerted significant positive effects on adoption, with perceived usefulness showing a stronger effect. This pattern suggests that while both dimensions matter, farmers in mountainous areas prioritize practical benefits (time savings, health protection, effectiveness) over ease of operation. The stronger PU effect aligns with the rigid demand context: when manual spraying is highly dangerous and inefficient, usefulness concerns outweigh ease-of-use considerations. These findings suggest that information obtained by farmers through social media platforms, including drone application cases and effectiveness demonstrations, not only helped them recognize the practical value of the technology but also reduced concerns about technological complexity. Overall, technology cognition, as a partial mediator, reveals the underlying mechanism through which social media influences technology adoption: social media both directly reduces information search costs and provides social demonstration effects (direct effect), and indirectly promotes adoption by altering farmers' technology cognition (indirect effect).

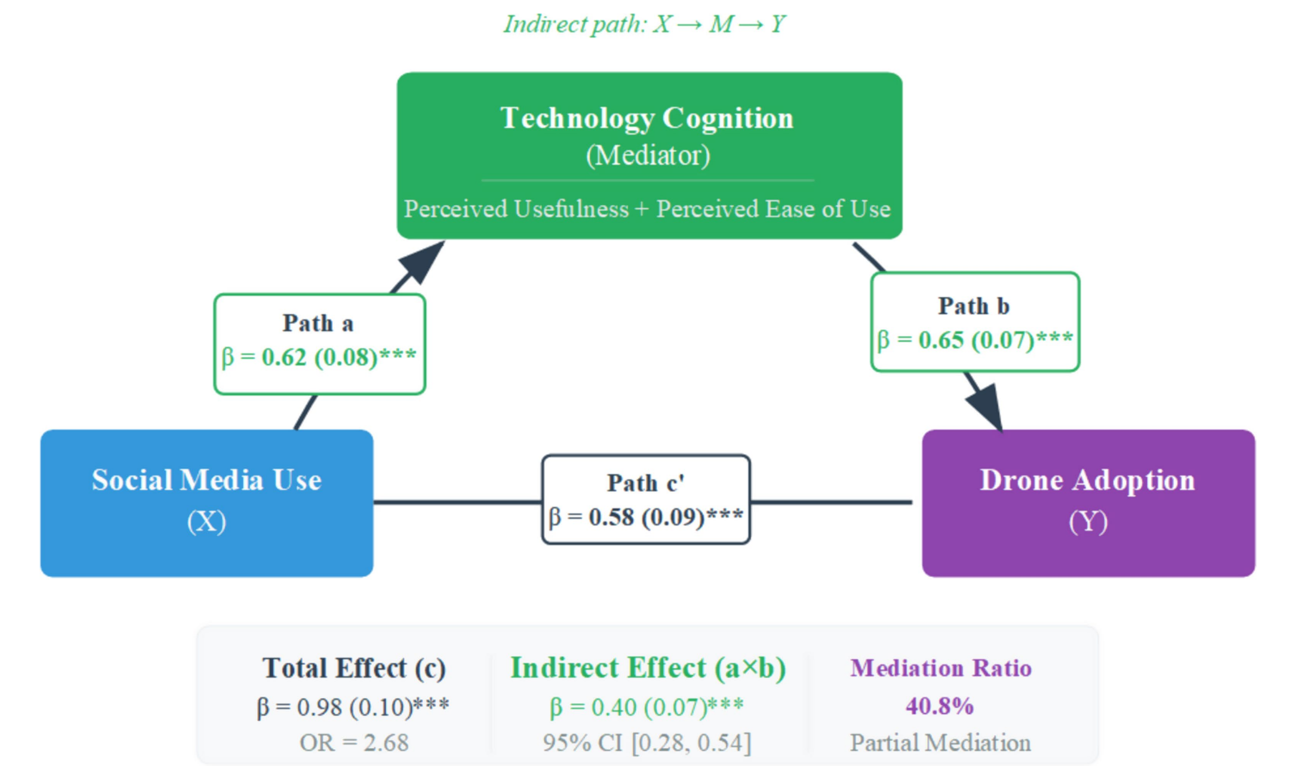

FIGURE 3
Mediation path analysis. Standardized coefficients reported. Standard errors in parentheses. ***$p < 0.001$. Bootstrap 5,000 resamples.

3.4 Moderation effect analysis

To examine the moderating role of terrain complexity on the relationship between social media and drone adoption, interaction terms (social media × terrain type) were introduced into the baseline model (Equation 5). The regression results showed that the interaction term coefficient was 0.28 ($p < 0.01$), indicating that terrain complexity significantly strengthened the promoting effect of social media on adoption, confirming the moderation effect. To further reveal this moderating mechanism, subsample regressions were conducted by terrain type. The grouped regression results demonstrated that the effect of social media on adoption exhibited a significant increasing trend with terrain complexity: the OR value was 1.51 in plain areas ($\beta = 0.41$, $p < 0.05$), 2.44 in hilly areas ($\beta = 0.89$, $p < 0.001$), and reached 4.14 in mountainous areas ($\beta = 1.42$, $p < 0.001$). The social media effect in the mountainous group was 2.74 times that of the plain group (4.14/1.51); this difference was confirmed to be statistically significant through simple slope tests ($\chi^2 = 18.3$, $p < 0.001$).

Based on grouped Logit regression models, predicted adoption probabilities were calculated for each terrain type at different social media use levels, with results presented in Figure 4. The horizontal axis represents social media use intensity (from low to high), the vertical axis represents the predicted probability of drone adoption, and the three curves represent plain, hilly, and mountainous terrain, respectively. At lower social media use levels (10th percentile), the differences in adoption probability across the three terrain types were relatively small (plain 15%, hilly 22%, mountainous 28%). However, as social media use intensity increased to high levels (90th percentile), the differences expanded significantly: adoption probability in plain areas increased to 35% (an increase of 20 percentage points), in hilly areas reached 58% (an increase of 36 percentage points), and in mountainous areas reached 72% (an increase of 44 percentage points). The slope for the mountainous group was noticeably steeper than the other two groups, indicating that social media has a stronger marginal effect in mountainous environments.

This moderation effect can be attributed to three mechanisms. First, manual plant protection operations in mountainous orchards are highly dangerous and costly; drone technology represents a rigid demand rather than an optional choice for mountainous farmers, who are therefore more sensitive to technical information. Second, transportation inconvenience in mountainous areas makes traditional agricultural extension coverage difficult; social media has become the primary or even sole channel for mountainous farmers to obtain technical information, resulting in a stronger information substitution effect. Third, mountainous fruit trees (apples, citrus) have higher economic value, and the efficiency improvements brought by drones generate more significant economic returns, strengthening farmers' motivation to learn and adopt technology through social media. These findings indicate that agricultural technology extension policies should fully consider terrain heterogeneity, with priority given to deploying social media-based digital extension channels in mountainous and hilly areas.

3.5 Robustness checks

To verify the reliability of baseline regression results, multiple robustness checks were conducted, with results presented in Table 4. First, to address potential endogeneity concerns, the instrumental variable two-stage least squares (IV-2SLS) method was employed (Equations 6–7). Using county-level internet penetration rate in 2010 as the instrumental variable, the first-stage F statistic was 31.8, far

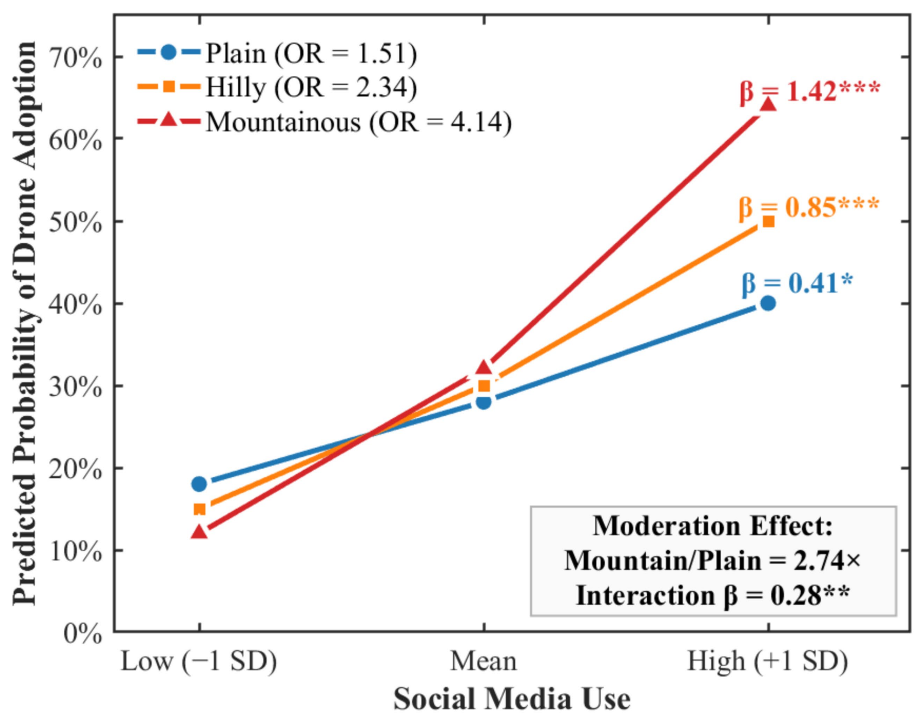

FIGURE 4
Terrain moderation effect. Predicted probabilities at ±1 SD of social media use. *p < 0.05, **p < 0.01, ***p < 0.001.

TABLE 4 Robustness test results.

Method	Coefficient/OR	SE	p-value	95% CI
Endogeneity treatment				
IV-2SLS (First stage F)	$F = 31.8$	—	<0.001	—
IV-2SLS (Second stage)	$\beta = 0.52$	0.12	<0.001***	[0.28, 0.76]
PSM-ATT	ATT = 0.31	0.06	<0.001***	[0.19, 0.43]
Alternative dependent variable				
Ordered Probit (adoption intention)	$\beta = 0.48$	0.09	<0.001***	[0.30, 0.66]
Alternative moderator				
Continuous slope × Social media (interaction)	$\beta = 0.018$	0.006	0.003**	[0.006, 0.030]
Subsample analysis				
Mountainous only (n = 300)	OR = 4.38	0.85	<0.001***	[2.95, 6.49]

IV, county-level internet penetration rate in 2010. PSM uses 1:1 nearest neighbor matching; all standardized biases <5% after matching. *, **, *** indicate significance at 10, 5, and 1% levels, respectively.

exceeding the critical value of 10, indicating sufficient instrument strength; the second-stage regression (Equation 7) showed a social media coefficient of 0.52 (p < 0.001), consistent with the baseline model conclusions (see Supplementary Appendix F for complete first-stage regression results and instrument diagnostics) Second, propensity score matching (PSM) was employed to control for selection bias; after 1:1 nearest neighbor matching, sample balance was satisfactory (all standardized biases <5%), and the average treatment effect on the treated (ATT, calculated using Equation 8) was 0.31 (p < 0.001), confirming the robustness of the causal effect of social media on adoption (see Supplementary Appendix G for detailed covariate balance tests).

As shown in Table 4, the tests with alternative dependent variables also supported the main conclusions. When actual adoption (binary variable) was replaced with adoption intention (1–5 scale) and estimated using an Ordered Probit model, the social media coefficient was 0.48 (p < 0.001), with the direction and significance of the effect remaining consistent. In the test replacing the moderating variable, when continuous slope (degrees) replaced the categorical terrain variable, the interaction term coefficient was 0.018 (p < 0.01), indicating that each one-degree increase in slope was associated with a 1.8% increase in the marginal effect of social media, further verifying the robustness of the terrain moderation effect. Finally, regression using only the mountainous subsample (n = 300) yielded an OR value of 4.38 (p < 0.001) for social media, higher than the full-sample estimate, once again confirming the enhanced effect of social media in mountainous environments. In

TABLE 5 Regional heterogeneity analysis.

Region	Crop type	*N*	Terrain composition	Avg. slope	Adoption rate	Social media OR	Tech cognition β	Mediation %
Shaanxi	Apple	300	80% M, 17% H, 3% P	16.2°	48.9%	3.77*** (0.64)	0.69*** (0.10)	43.5%
Yunnan	Banana/ Mango	220	23% M, 64% H, 14% P	11.4°	42.8%	2.77*** (0.52)	0.61*** (0.09)	40.2%
Hunan	Citrus	130	8% M, 23% H, 69% P	6.2°	27.1%	1.93** (0.35)	0.56** (0.08)	41.8%
Between-group difference	–	650	–	$F = 428.5$***	$\chi^2 = 32.8$***	$\chi^2 = 24.6$***	$F = 6.8$**	–

M, Mountainous; H, Hilly; P, Plain. Standard errors in parentheses. **, *** indicate significance at 5 and 1% levels, respectively. OR values from grouped Logit regressions controlling for age, education, income, and orchard size. Mediation % calculated using Bootstrap method (5,000 replications). Terrain composition percentages based on sample distribution within each province.

summary, the main research conclusions passed multiple robustness checks and demonstrate high credibility.

3.6 Regional and demographic heterogeneity

To explore contextual variations, we conducted subsample analyses across the three provinces. Regional analysis revealed substantial variation in social media effects, reflecting differences in terrain complexity and information accessibility (Table 5). Social media's effect was strongest in Shaanxi (OR = 3.77, $p < 0.001$), where the dominance of loess plateau mountainous terrain (80% of samples with average slope 16.2°) creates strong demand for alternative information channels. The effect was moderate in Yunnan (OR = 2.77, $p < 0.001$), where mixed terrain (64% hilly, 23% mountainous) presents intermediate accessibility challenges. The effect was weakest in Hunan (OR = 1.93, $p < 0.01$), where predominantly hilly and plain terrain (69% plain, 23% hilly, average slope 6.2°) allows better coverage by traditional extension services. The mediation ratio of technology cognition ranged from 40.2 to 43.5% across regions, indicating that the psychological mechanism operates consistently despite varying effect magnitudes. These regional patterns strongly support our terrain moderation hypothesis: provinces with more mountainous terrain exhibit stronger social media effects due to greater information constraints and rigid demand for labor-saving technologies.

Demographic heterogeneity analysis showed that social media effects were significantly stronger among younger farmers (<50 years: OR = 3.24 vs. ≥50 years: OR = 2.01, between-group difference $p < 0.05$), reflecting younger cohorts' greater digital literacy and information processing capacity. Education level also moderated the effect: farmers with high school education or above showed stronger social media effects (OR = 3.45) compared to those with junior high school education or below (OR = 2.08, between-group difference $p < 0.01$). This pattern suggests that formal education enhances farmers' ability to extract actionable insights from social media content, transforming information exposure into adoption decisions. These findings indicate that social media-based extension strategies should be complemented with targeted support for older and less-educated farmers to ensure equitable technology access. Specifically, extension programs could provide smartphone navigation training and simplified agricultural content formats (emphasizing visual demonstrations over text) to bridge the digital divide and maximize the inclusive benefits of digital extension in mountainous regions.

4 Discussion

This study systematically analyzed the ways in which social media use influences the adoption of plant protection drones among mountainous fruit farmers, based on a sample size of 650 from Yan'an (Shaanxi), Yunnan, and Hunan provinces. The results reflected that the use of social media significantly facilitates the adoption of drones among mountainous fruit farmers, with an OR value of 2.68 and $p < 0.001$; therefore, compared to their non-using counterparts, the probability of adoption by social media users was 34 percentage points higher. Technology cognition, as a mediating variable, explained 40.8% of the total effect. Terrain complexity significantly amplified the effect of social media, and the mountainous effect was 2.74 times that of plain areas. These conclusions were verified by instrumental variable methods, propensity score matching, and other approaches, and the conclusions were robust. This study makes three key contributions to agricultural technology adoption research: validating TAM's applicability in mountainous agricultural contexts where perceived usefulness ($\beta = 0.38$) and perceived ease of use ($\beta = 0.24$) mediate social media's effect; identifying terrain complexity as a critical moderator that amplifies digital media effects under information constraints; and demonstrating that social media can partially substitute for traditional extension services in geographically challenged areas, as evidenced by regional variation analysis showing effects ranging from OR = 1.93 in plain-dominated Hunan to OR = 3.77 in mountainous-dominated Shaanxi. Hamza et al. (2025) also proved the positive effect of social media on farmers' income through empirical research in Pakistan, where the technical efficiency of the social media user group improved by 18.86%.

Social media promotes drone adoption via multiple pathways. The visual demonstration of technology in short videos effectively lowers the threshold for understanding and mastering the technology. In 2023, there were around 27.8 million agricultural technology videos published on China's Douyin platform, which gained 120.6 billion views. Agricultural technology short videos have hence become one important channel for farmers to obtain technical information (Xinhua, 2024). Peer experience sharing, meanwhile, enhances the trust of farmers in new technologies. Dilleen et al. (2023) show that social media effectively alleviates the trust deficit of farmers in new technologies, by facilitating knowledge dissemination and the information sharing of farmers. Real-time interactive functions provide channels for the timely resolution of farmers' technical problems. This work verifies the mediating effect of technology cognition and, thus, validates the applicability of the Technology Acceptance Model (TAM) in agricultural contexts. That result supports Yu et al.'s (2024) research on the impact of digital multimedia in regard to the adoption of agricultural green production technology, showing that digital media promotes technology adoption through enhancing the perceived usefulness and perceived ease of use of farmers. Dai and Cheng (2022) showed that social networks will significantly influence the choice behavior of farmers in the adoption of agricultural green production technologies positively, and this effect is realized by perceived usefulness and perceived ease of use.

The amplification of social media effects through mountainous terrain can be explained from multiple dimensions. From the perspective of rigid demand characteristics, manual plant protection in mountainous orchards is highly dangerous and inefficient. The adoption of drone technology represents a rigid necessity rather than a discretionary choice of mountainous farmers. As pointed out by a World Bank (2022) report, mechanization promotion in mountainous and hilly areas is an important technical support to ensure agricultural industry prosperity and poverty alleviation. From the perspective of information substitution effects, transportation inconvenience in mountainous areas makes traditional agricultural extension coverage quite difficult. Social media has thus turned out to be the main or even the sole channel for mountainous farmers to acquire technical information. According to Ali et al. (2023), a study in the Hindu Kush Himalayan region found that contact with agricultural extension services significantly influences farmers in the adoption of technology, but mountainous farmers generally face the problem of insufficient extension service coverage. Economic incentives are another critical driving factor. Mountainous fruit trees, such as Yan'an apples and Hunan citrus, have higher added values, and improvements in efficiency brought about by drones created bigger economic returns. In accordance with Quan et al. (2023), based on the research on more than 2,000 grain farmers across 11 Chinese provinces, it was found that drone adoption increases farmers' income by 434–488 USD per hectare, simultaneously reducing plant protection operation time significantly. It is worth mentioning that in general, agricultural mechanization in hilly and mountainous areas faces certain challenges: only 76.41% of the arable land has reached basic suitability or above (Yang et al., 2023). According to related studies, Yan et al. (2024) stated that mechanization has significant effects on the environmental efficiency in plain and hilly areas but the effects are not significant in mountainous areas.

Our results both show consistencies and differences with existing literature. Similar to the study of Zheng et al. (2021) on plant protection drone adoption by Chinese grain farmers, this study confirms the significant driving role of TAM core variables (perceived usefulness and perceived ease of use) in adoption behavior. The terrain moderation effect, however, is revealed in this study and extends existing understanding. The advantages of information dissemination through social media are more salient in mountainous terrain and thus contrast sharply with studies involving plain grain crops. Yadav et al. (2023), in their analysis of Twitter data, show that social media is an important method of disseminating agricultural technology. This study further demonstrates the applicability of this effect within the mountainous fruit tree sector with effect magnitude moderated by terrain. Kendall et al. (2022), in their study on the adoption of precision agriculture technology among small-scale family farms in China, identified cost, insufficient subsidies, and land fragmentation as major adoption barriers. Our findings indicate, however, that social media can overcome these obstacles partially.

This research also provides important implications for policy formulation. At the level of extension strategy, it is suggested that deploying social media-based agricultural technology extension channels in mountainous and hilly regions should be prioritized. Given that social media effects are 2.74 times stronger in mountainous areas, agricultural authorities should allocate digital extension resources preferentially to terrain-constrained regions where traditional services face high costs. Setting up officially certified platforms of short videos on agricultural technology and fully making use of the comparative advantages of social media in information dissemination is necessary. In terms of the subsidy mechanism, it may be considered to provide more training subsidy policies or lower down-payment thresholds for farmers who learn and adopt drone technology through social media, thus stimulating farmers to get technical information themselves. For instance, offering differentiated subsidy rates (higher in mountainous areas) can account for greater adoption barriers while leveraging social media's information diffusion capacity. At the level of content governance, setting standards in terms of quality should be done for agricultural technology video content. Expert review mechanisms should be established, and the spread of misleading information affecting farmer decision-making should be avoided. Additionally, demographic heterogeneity analysis revealed that social media effects are stronger among younger and more educated farmers; therefore, extension programs should integrate digital literacy training (smartphone navigation, content evaluation skills) to ensure equitable technology access across age and education groups. These recommendations directly respond to the "low-altitude economy empowering rural revitalization" strategy put forward in the Central Committee of the Communist Party of China and State Council, 2025. and provide empirical support for digital transformation in mountainous agriculture. As Cui and Wang (2023) pointed out, farmers' digital technology adoption would be influenced by many factors from such dimensions as socioeconomic, agroecological, technological, institutional, psychological, and behavioral. Policy formulation therefore needs to comprehensively consider the interactions among such dimensions.

Several limitations exist in this study and should be acknowledged. Regarding measurement, we combined perceived usefulness and perceived ease of use into a single technology cognition construct based on context-specific considerations (farmers' qualitative responses showed conflation of the two concepts, and high correlation $r = 0.68$ suggested a unified cognitive dimension). While this approach maintains analytical parsimony and demonstrated good reliability (Cronbach's $\alpha = 0.87$), it represents a departure from traditional TAM applications that analyze these dimensions separately. Additionally, our use of logistic regression for mediation testing, though appropriate for binary outcomes and validated through Bootstrap methods (5,000 replications), has limitations compared to structural equation modeling. Specifically, our approach does not formally test measurement models via confirmatory factor analysis or estimate measurement error, which may introduce slight bias in effect estimates. Future research employing SEM could address these limitations and formally validate the factor structure of technology cognition in agricultural contexts. The cross-sectional data cannot capture the dynamic adoption process, though instrumental variable analysis (using 2010 internet penetration rates) and propensity score matching help address reverse causality concerns. Longitudinal surveys tracking farmers over time would strengthen causal inferences and reveal how information accumulation influences adoption timing. This research did not differentiate the effects of different social media platforms such as Douyin versus Kuaishou, nor was the specific influence of video content quality on adoption measured. Our composite social media use index captures overall exposure but masks platform-specific mechanisms and content characteristics that may differentially affect adoption. Furthermore, while regional heterogeneity analysis demonstrates varying effects across provinces, the terrain-based (rather than province-based) sampling strategy limits definitive province-specific conclusions. Longitudinal surveys and content analysis methods may be employed in future research to further deepen these topics.

5 Conclusion

This study shows that social media platforms facilitate the adoption of agricultural technology in mountainous areas. Based on survey data from a sample size of 650 fruit farmers across three Chinese provinces, social media use positively influences drone adoption probability, with an odds ratio of 2.68, while technology cognition mediates 40.8% of this effect. Terrain complexity moderates the influence of social media; the effect among mountainous farmers is 2.74 times that of plain farmers. Regional heterogeneity analysis further reveals that social media effects vary systematically with terrain composition, ranging from OR = 1.93 in plain-dominated Hunan to OR = 3.77 in mountainous-dominated Shaanxi, supporting the terrain moderation mechanism. These findings imply that in information-constrained environments, digital platforms could help close the technology adoption gap that traditional extension services struggle to reach. Social media tends to cut down on information search costs and shapes farmers' cognitive perceptions concerning new technologies, hence adoption decisions. This study extends the Technology Acceptance Model to mountainous agricultural contexts and underlines the potential importance of terrain heterogeneity in technology diffusion research. For the policymakers, the findings indicate that social media can be employed as a supplementary channel for agricultural technology extension in mountainous areas. As China implements its rural revitalization strategy, digital platforms have the potential to act as valuable assistants for smallholders in geographically challenged regions toward agricultural modernization.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

Ethical approval was not required for the studies involving humans because the studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

PZ: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft. HW: Conceptualization, Funding acquisition, Project administration, Resources, Supervision, Writing – review & editing.

Funding

The author(s) declared that financial support was not received for this work and/or its publication.

Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2026.1755351/full#supplementary-material

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