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Examining farmers' intention to use drone applications in agricultural production

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Abstract

Digitalization in agriculture involves the integration of technological innovations across the entire supply chain, from production through distribution to consumption. This paper examines drone applications and farmers' intentions to use them in an emerging economy. This study uses correlation analysis and structural equation modeling to analyze the data collected from 414 Vietnamese farmers. The empirical results indicate that drone compatibility and speed positively impact farmers' desires and anticipated emotions, whereas risks negatively influence both desires and emotions. These findings also show that farmers' desires and emotions towards drones have pushed their intentions to use them. Notably, the environmental friendliness of drones plays a moderating role in strengthening the relationship between farmers' desires, emotions, and intentions. Surprisingly, drone complexity does not have a significant impact on leading farmers' desires and emotions. These findings contribute to a deeper understanding of the factors influencing the adoption of digital technologies in agriculture and provide valuable insights for policymakers and stakeholders seeking to promote the integration of drones into agricultural practices.

Keywords: Digitalization, Environmental protection, Innovation, Agricultural production, Drone application

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1. Introduction

Advancements in science and technology have introduced various new technologies that support diverse fields. One significant innovation is the drone (Unmanned Aerial Vehicle - UAV) (Ellenberg *et al.*, 2014). Beyond its initial military applications, drones have undergone significant development and are now extensively utilized in numerous sectors, such as industry, agriculture, and delivery services (Renduchintala *et al.*, 2019). In modern agriculture, drone technology is not just a tool but a revolutionizing force transforming the industry. It offers novel solutions that enhance production efficiency, boost productivity, and cut costs. Consequently, this study examines how the application of drones in agriculture influences farmers' adoption intentions.

Drone technology is increasingly integrated into agriculture, offering sophisticated solutions for monitoring crops and livestock. Drones can hover above fields, capturing aerial images and videos that help farmers assess crop growth, identify early signs of pests and weeds, and monitor the health and whereabouts of livestock. Previous studies, such as Ahirwar *et al.* (2019), have explored the application of drones in agriculture. However, questions remain regarding customer desire, emotions, and intentions to adopt drones in emerging economies. Dutta and Goswami (2020) highlighted how drone technology supports farmers in enhancing productivity and quality through efficient water and pesticide use while maintaining soil fertility. Rejeb *et al.* (2022) also discussed drones' roles in remote sensing, precision agriculture, and machine learning.

The studies mentioned have contributed to the literature on initial drone adoption insights, focusing primarily on emerging economies. This paper expands upon this by analyzing farmers' adoption intentions within an emerging economy context. Additionally, none of the studies mentioned above have investigated whether the environmental friendliness of drones enhances farmers' intentions (Yoo *et al.*, 2018; Sah *et al.*, 2021). In addition to applying the diffusion of innovation theory to new technology adoption, this study incorporates the model of Chi *et al.* (2023) on drone delivery to explore the factors influencing drone adoption in emerging economies.

Vietnam serves as the empirical setting to explore how drone technology influences farmers' adoption intentions. From 2021 to 2022, the Plant Protection Department collaborated with accredited testing organizations and local aircraft suppliers to conduct trials of drone spraying models. These tests covered seven main crop groups and utilized eight types of pesticides to combat 15 different pests across various agricultural regions nationwide. The findings indicate high potential for drone technology in pesticide spraying, particularly effective for crops such as rice, maize, and fruit trees. Additionally, drones significantly reduce water usage and labor costs compared to conventional methods. Participants in these trials reported reduced pesticide exposure compared to traditional spraying techniques (Chi, 2024; Pham *et al.*, 2023). However, operational challenges persist, including weather conditions, terrain, and traffic congestion. Therefore, this study aims to investigate how drones impact farmers' intentions to integrate them into their agricultural practices.

The remainder of this article is structured as follows. Section 2 outlines the theoretical framework and hypotheses. Sections 3 and 4 present research methods and results, respectively. Finally, sections 5 and 6 reveal the study's implications and conclude the paper.

2. Theoretical framework

2.1 Drone application in agriculture

Agricultural drones, unmanned aerial vehicles controlled remotely, play a crucial role in farming by monitoring crop growth and assisting farmers in optimizing fertilization techniques (Puri *et al.*, 2017). Drones, equipped with advanced sensors and digital cameras, capture detailed images of expansive fields and provide farmers with valuable data (Ahirwar *et al.*, 2019). This information is instrumental in refining fertilization methods, seed sowing, and pesticide spraying, thereby reducing labor requirements and enhancing farm efficiency (Dutta and Goswami, 2020).

Several previous scholars have suggested frameworks in technology adoption and acceptance, such as the diffusion of innovation (DOI) of Rogers *et al.* (2019), the theory of planned behavior (TPB) of Fishbein and Ajzen (1977), the unified theory of acceptance and use of technology of Venkatesh *et al.* (2003). In general technology adoption, Rogers *et al.* (2019) suggested that the main factors in adopting new technology systems which are compatibility, complexity, trialability, and observability. This theory is often used in information and communication systems research to understand why consumers adopt innovative technologies. Most researchers have applied DOI using the technology acceptance model (TAM) introduced by Davis (1989). TAM is used to explain and predict the level of technology acceptance (Moon and Kim, 2001). According to TAM, perceived usefulness and ease of use are important factors influencing attitude and behavioral intention towards using the system (Vijayasarathy, 2004). Meanwhile, regarding drone application, Yoo *et al.* (2018) proposed the important influences of compatibility, complexity, speed, and risk on attitude and intention to use drone delivery in the retail industry. Drawing from the frameworks suggested by Rogers *et al.* (2019) and Yoo *et al.* (2018), this study employed DOI and the framework of drone delivery to investigate the impact of drone attributes (in terms of compatibility, complexity, relative advantage of speed, and risks) on farmers' intention to use drone in farming.

According to Rogers (1983), compatibility is defined as "the degree to which an innovation" is "perceived as being consistent" with "the existing values, needs, past experience of potential users" while complexity is "the degree to which an innovation" is "perceived as being difficult to adopt". Relative advantage is considered "the degree to which an innovation" is "perceived as being better than its competitors" (Rogers, 1983).

2.2 Desire, anticipated emotion, and intention to use

Desire, according to Perugini and Bagozzi (2004), denotes the internal motivation of an individual to perform actions or achieve specific goals. They emphasize that decision-making motivation is shaped by the desire to engage in certain behaviors and to facilitate intention formation. Building upon this framework, Bagozzi (2007) developed the goal-directed behavior (MGB) model, validating motivational theories and their application to technology adoption by examining customer desires. Leone *et al.* (1999) assert that desire serves as a direct precursor to intention, whereas attitude acts as a more distant influencer.

Perceived risk (PR) is defined as "consumers' subjective assessment of the likelihood and consequences of a specific purchase decision" (Cox and Rich, 1964). Taylor (1974) describes perceived risk specifically in terms of potential loss. When considering the use of drone delivery services, perceived risk, as posited by Klauser and Pedrozo (2017), reflects the subjective evaluation of potential losses associated with such services.

2.3 Hypothesis development

2.3.1 Effect of drone factors on desire

Boateng *et al.* (2016) suggested that "lifestyle is the search for coherence and compatibility in different aspects of life". Lee and Lee (2020) showed that "users ask for more than just traditional values of reasonable price, good quality, speed of service and customization". Lee (2019) also argued that "users want to be at the center of value creation activities, seeking new experiences, participating in the co-creation of shared goals and hedonic attributes such as a sense of beauty and security, flow, stimulation and enjoyment". Hence, farm households have to adopt innovative technology to enhance their capabilities and adapt to "the changing environment" with speed and compatibility (Das *et al.*, 2022). Firms implement innovation to create value, such as greater speed and co-innovation (Lee and Olson, 2010). From this respect, the compatibility of drones will make farmers desire to use this technology. Consequently, the following hypotheses are suggested:

H1a: Drone compatibility positively affects farmers' desire.

H2a: Lower complexity positively affects farmers' desire.

H3a: The speed of drones positively affects farmers' desire.

H4a: Risks have a negative impact on farmers' desire.

2.3.2 Effect of drone factors on anticipated emotion

According to Tan and Teo (2000), a highly complex technology system requires much effort to operate. Complexity is "similar to perceived ease of use" which impacts users' emotions in the TAM (Yoo *et al.*, 2018). Several studies have suggested the impact of complexity on innovative service applications (López-Nicolás *et al.*, 2008; Hwang *et al.*, 2019; Nam and Luu, 2022). Customers who perceive drones as less complex will have positive emotions.

According to Luppicini and So (2016), as more than 80% of drone operations take place below 120 m (Ren and Cheng, 2020), the risks are a concern when drones are developed and adopted. Subsequently, several scholars have investigated the perceived risks of drones in different countries (e.g., Mathew *et al.*, 2021). Users have higher expectations for new technology but also show negative attitudes when use leads to undesirable adverse consequences. They can receive higher risks because of lacking trust (Zhu *et al.*, 2009). The "probability of a drone malfunctioning" and "being unable to deliver a product" can affect the users' emotions (Sah *et al.*, 2021). Users have negative feelings because of the possible risks of innovative technology (Sun, 2021). Therefore, it can be suggested that the risks of drones may create negative anticipated emotion of farmers. Consequently, the following hypotheses are proposed:

H1b: Compatibility of drone positively affects anticipated emotion.

H2b: Lower complexity of drone positively affects anticipated emotion.

H3b: The speed of drone positively affects anticipated emotion.

H4b: Risks have a negative impact on anticipated emotion.

2.3.3 Effect of desire and anticipated emotion on customer intention to use

Desire to join certain behavior is the most important factor influencing intention/behavior (Perugini and Bagozzi, 2004). Several prior studies have also demonstrated the role of desire in understanding the user intention towards technology usage (Bagozzi, 2007; Hwang *et al.*, 2019; Osakwe *et al.*, 2022). Therefore, it can be suggested that desire is an important factor in farmers' intentions (Hwang and Kim, 2021). Consequently, the following hypotheses are proposed:

H5: Desire has related significantly to farmers' intention to use drone delivery services.

H6: Anticipated emotion has related significantly to farmers' intention to use drones.

2.3.4 The moderating role of environmental friendliness

Lee *et al.* (2016) suggested that drone delivery services offer many benefits, such as "faster speed", "lower maintenance cost", and "environmental friendliness". Meanwhile, innovation in information technology adoption become an important point for businesses in various industries (Suzuki *et al.*, 2014). Rose (2013) first argued that drones are more environmentally friendly than trucks or motorbikes, attracting consumers who often take care of the environment. Drone delivery "could be more environmentally friendly than truck using simulation" (Goodchild and Toy, 2018). They compared carbon dioxide emissions generated by drones and truck deliveries, looking at allowable energy requirements, the number of delivery stops, and the size of regional service. The results show that drone delivery emits less carbon than trucks, has fewer stops when the business area is closer to the warehouse, and has a higher allowable energy level. Drones are battery-operated and, therefore, do not emit carbon like trucks. Drones will also reduce the traffic congestion contributed by traditional deliveries and personal trips to stores. Users agree that drone deliveries can be environmentally friendly (Soffronoff *et al.*, 2016). Consequently, it can be concluded that the environmental friendliness of drones transforms farmers' desire and emotions into their intention to use drones in agriculture. Therefore, the following hypotheses are developed:

H7a: The environmental friendliness of drones strengthens the relationship between farmers' desires and their intention to use them.

H7b: The environmental friendliness of drones strengthens the relationship between anticipated emotion and their intention to use.

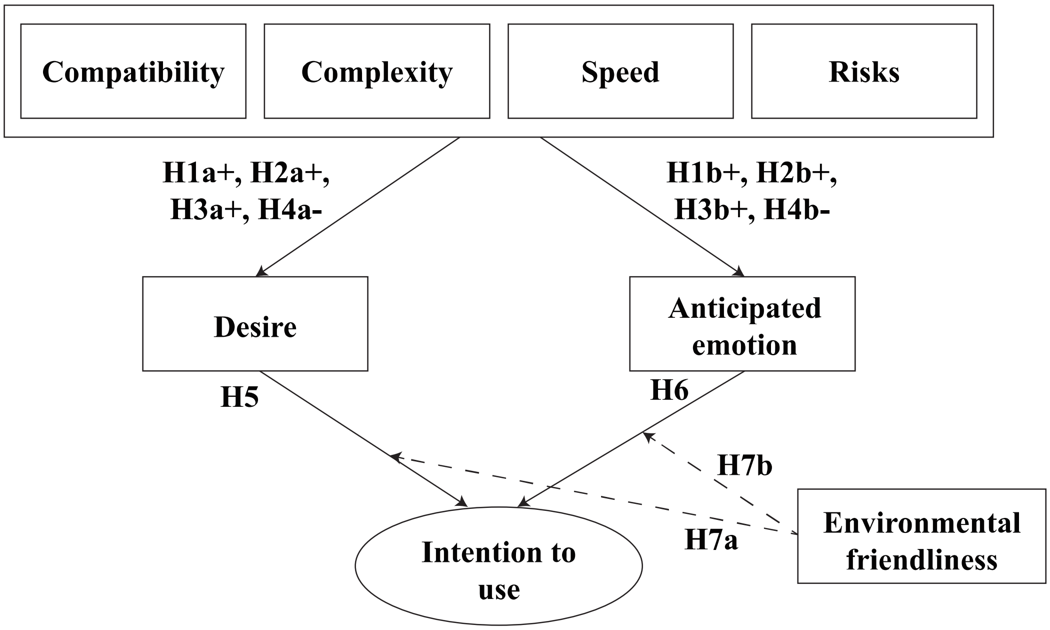

Figure 1. The proposed framework

Source: Authors' suggestion

3. Research methods

3.1 Measurement

This study employed a scale of measurement of proposed constructs (compatibility, complexity, speed, risks, desire, anticipated emotion, and intention to use) from previous studies that had been validated (Table 1). This proposed scale of measurement was conducted using a five-point Likert scale.

Table 1. The proposed scale of measurement

Constructs	Code	Items	Source
Complexity	COM1	My experiences with drone deliveries were straightforward and comprehensible.	Hwang *et al.* (2021)
	COM2	I expect drone delivery to efficiently fulfill my needs.	
	COM3	I find drone delivery user-friendly.	
Speed advantage	SPE1	Drone allows me to have high spraying efficiency.	Tan and Teo (2000)
	SPE2	Drone is a quick way to show seeds faster than the traditional way.	
	SPE3	Useful drone for quick fertilizing on farm.	

Table 1. The proposed scale of measurement (*continued*)

Constructs	Code	Items	Source
Compatibility	COP1	Using drones aligns with every aspect of my farm work. I believe that using drones meets my expectations in agricultural operations.	Yoo *et al.* (2018)
	COP2	Using drones aligns with every aspect of my farm work. I believe that using drones meets my expectations in agricultural operations.	
	COP3	I think using drones is necessary in agriculture.	
Risks	RIK1	Spraying pesticides can be risky.	Osakwe *et al.* (2022)
	RIK2	The types of seeds, when sown with a Drone, may not be uniform on the soil.	
	RIK3	Fertilization may take too long or may not be enough.	
Environmental friendliness	ENV1	There are thresholds to growth that our industrialized society cannot surpass. Humans must coexist harmoniously with nature to ensure survival.	Yoo *et al.* (2018)
	ENV2	There are thresholds to growth that our industrialized society cannot surpass. Humans must coexist harmoniously with nature to ensure survival.	
	ENV3	I think using drones is environmentally friendly.	
Desire	DES1	I want to use drone delivery because of its great benefits.	Osakwe *et al.* (2022)
	DES2	My desire to use drone because of cost-saving.	
	DES3	I want to use a drone to control the whole field.	
Anticipated emotion	EMO1	Using a drone would bring me happiness.	Hwang *et al.* (2020)
	EMO2	Using a drone would make me feel excited.	
	EMO3	Using a drone would fill me with delight.	
Customer intention to use drone service	INT1	I will use drone delivery to fertilize our crops.	Yoo *et al.* (2018)
	INT2	I intend to use a drone to sow seeds.	
	INT3	I intend to use drones to control our farm.	

Source: Authors' compilation

3.2 Population and sample

Regarding sample size, when accurate data are unavailable, previous studies often employed a comparable non-probability approach (Chen and Tsai, 2007). Hair *et al.* (2014) suggested that adequate structural equation modeling (SEM) analysis requires a sample size of at least 300. A probabilistic method determines the necessary sample size to make reliable inferences about the population. This study adheres to Horng *et al.* (2012) for calculating required samples, using a 95% confidence level and a ±0.05 margin of error in sampling. According to the General Statistics Office of Vietnam, there are 16.881 farmer households. Therefore, the required sample size for this study is 384.

This study distributed the questionnaire to 450 farmer households to get at least 400 responses. Farmers were selected from four places in the North of Vietnam to distribute questionnaires because these provinces have large agricultural areas and can apply technology in production. The participants in the survey were randomly chosen among farmers who live in Hanoi, Hoa Binh, Vinh Phuc, and Ninh Binh. We used the farm household lists obtained from the provincial governments to select respondents. Three collectors were recruited to deliver the survey to farmers from September to November 2022. Further, after each participant completed the questionnaire, they received a small financial incentive from the research project through the online bank transfer. This study followed a proper ethical procedure by ensuring that all participants' answers were kept confidential. In addition, all the questionnaires were anonymized. After launching the survey, this study collected 414 valid observations after the formal survey had been conducted. The percentage of females was higher than males (55% versus 45%). Most farm managers were under 50 years old and had over five years of experience. The majority of farmers had an educational background lower than a university degree and more than 10 years of farming experience (Table 2).

Table 2. Respondents' information

Information			Percentage (%)
Gender of farmers	Female	227	55
	Male	187	45
Age of farm manager	18-30	5	1
	31-40	112	27
	41-50	197	48
	Above 50	100	24
Education	Less than high school	345	83
	University	61	15
	Postgraduate	8	2
Farming experience	Under 5 years	91	22
	5-10 years	136	33
	10-20 years	157	38
	Above 20 years	30	7

Source: Authors' research sample

3.3 Data analysis

This study utilized SPSS AMOS 26 for data analysis. Firstly, confirmatory factor analysis (CFA) was employed to assess the reliability and validity of the proposed measurement scale. Secondly, covariance-based structural equation modeling (CB-SEM) was chosen to test the hypotheses. This approach was selected for two main reasons. Our research framework is confirmatory, following Hair *et al.* (2014), who recommend CB-SEM for such purposes. In addition, in studies with larger datasets (250 samples or more), the results from partial least squares SEM (PLS-SEM) and CB-SEM tend to yield similar outcomes (Rigdon *et al.*, 2017).

4. Results

4.1 CFA analysis for testing validity and reliability

Convergent validity assesses whether the observed variables of a latent variable are positively and strongly correlated. This is determined by examining both the factor loadings of the observed variables and the average variance extracted (AVE) (Hair *et al.*, 2010). The standardized loading factor indicates how well the latent variable explains each observed variable. A good standardized loading factor typically exceeds 0.5 (Hair *et al.*, 2010; Fornell and Larcker, 1981). According to Hair *et al.* (2010) and Fornell and Larcker (1981), factor loadings should ideally surpass 0.5, and Cronbach's Alpha should be above 0.6 for reliable measurement. In Table 3, the factor loadings of all five constructs exceed 0.65, Cronbach's Alpha values exceed 0.7, and the AVE values exceed 0.50. These indicators meet the acceptable criteria set forth by Hair *et al.* (2010) and Fornell and Larcker (1981), confirming the reliability and validity of the constructs presented in Table 3.

Table 3. Confirmatory factor analysis results

		λ *	Cronbach's Alpha	CR	AVE
Complexity (COM)			0.81	0.90	0.69
	COM1	0.89			
	COM2	0.82			
	COM3	0.72			
Speed advantage (SPE)			0.87	0.91	0.76
	EMP1	0.89			
	EMP2	0.82			
	EMP3	0.91			
Compatibility (COP)			0.89	0.93	0.82
	COP1	0.92			
	COP2	0.90			
	COP3	0.90			
Risks (RIK)			0.82	0.89	0.60
	RIK1	0.84			
	RIK2	0.82			
	RIK3	0.78			
Environmental friendliness (ENV)			0.88	0.91	0.76
	ENV1	0.89			
	ENV2	0.85			
	ENV3	0.88			

Table 3. Confirmatory factor analysis results (*continued*)

		λ *	Cronbach's Alpha	CR	AVE
Desire (DES)			0.91	0.93	0.82
	DES1	0.92			
	DES2	0.90			
	DES3	0.89			
Anticipated emotion (EMO)			0.87	0.93	0.78
	EMO1	0.90			
	EMO2	0.88			
	EMO3	0.85			
Customer intention to use drone service (INT)			0.90	0.92	0.77
	INT1	0.87			
	INT2	0.85			
	INT3	0.85			

Source: Authors' calculation

Table 4. Mean, SD, and discriminant validity

	Mean	SD	Inter-construct correlations							
			COM	SPE	COP	RIK	ENV	DES	EMO	INT
Complexity	4.17	1.33	**0.83**							
Speed	4.37	1.19	0.63	**0.87**						
Compatibility	4.26	1.04	0.61	0.61	**0.90**					
Risks	3.22	1.27	0.67	0.33	0.37	**0.78**				
Environment friendliness	4.31	1.43	0.59	0.59	0.59	0.66	**0.87**			
Desire	4.79	1.22	0.65	0.61	0.65	0.67	0.69	**0.91**		
Anticipated emotion	4.73	1.08	0.46	0.53	0.52	0.22	0.50	0.51	**0.88**	
Intention to use	4.21	1.24	0.54	0.54	051	0.38	0.52	0.62	0.60	**0.88**

Notes: *All correlations are significant at a p-value less than 0.05; Boldfaced entries display the square root value of AVE scores for the latent constructs; SD is the standard deviation

Source: Authors' calculation

Discriminant validity is determined by comparing the square root coefficient of the observed variable scale used to measure a latent variable with the correlation coefficients between that latent variable and other latent variables (Fornell and Larcker, 1981). The average variance extracted (AVE) is the average level of explanation of the latent variable to its observed variables. If the square root of the average variance extracted sq coefficient is more significant than the remaining correlation coefficients, we conclude that the scale ensures discriminant validity (Fornell and Larcker, 1981). Table 4 shows that the square root of the average variance extracted SQRT(AVE) values are above 0.7, indicating strong discriminant validity among the constructs.

4.3 Hypotheses testing

CB-SEM was employed to test seven hypotheses. The theoretical model demonstrates a good fit with a Chi-square value of 2.044, GIF of 0.927, CFI of 0.920, and RMSEA of 0.050. These fit indices closely align with those of the measurement model, indicating a strong overall fit. The study supports the hypotheses H1a, H2a, H2b, H3a, H4a, H4b, and H5, while hypotheses H1b and H3b are not supported (see Table 5).

Table 5. Direct effect testing results

Hypothesis	Relationships			Path Coefficient (β)	P-value	Test result
H1a	Compatibility	→	Desire	0.33	0.00	Supported
H2a	Complexity	→	Desire	-0.11	0.42	Not Supported
H3a	Speed	→	Desire	0.46	0.00	Supported
H4a	Risks	→	Desire	- 0.41	0.00	Supported
H1b	Compatibility	→	Anticipated emotion	0.31	0.00	Supported
H2b	Complexity	→	Anticipated emotion	-0.08	0.17	Not Supported
H3b	Speed	→	Anticipated emotion	0.60	0.00	Supported
H4b	Risks	→	Anticipated emotion	-0.35	0.00	Supported
H5	Desire	→	Intention to use	0.41	0.00	Supported
H6	Anticipated emotion	→	Intention to use	0.55	0.00	Supported

Source: Authors' calculation

Drone compatibility, speed, and risks all affect farmers' desire and emotion toward drones in agriculture (p-value less than 0.05), while complexity does not have an impact on desire and anticipated emotion (p-value greater than 0.05). Drone speed has the highest impact on farmers' desire and emotions, while the effects of risks are negative. Regarding farmers' intention to use drones, anticipated emotion is considered to have a more significant impact on farmer intention than farmer desire.

4.4 Moderating effect analysis

A multi-group SEM analysis was conducted to examine the proposed moderating effects outlined in hypotheses H7a and H7b. Participants were divided into two groups based on the median splits of the moderator variable. Path coefficients were robust in both groups, but the association was notably stronger between desire and high environmental friendliness, confirming H7a. Additionally, environmental friendliness had a significant positive moderation effect on the relationship between anticipated emotion and intention to use (p-value less than 0.05), supporting H7b.

Table 6. Moderating effects

Hypothesis				Environmental friendliness		$\Delta\chi^2$ (df=1)	P-value	Result
				High	Low			
H7a:	Desire	→	Intention to use	0.42	0.32	8.03**	<0.05	Supported
H7b:	Emotion	→	Intention to use	0.36	0.28	6.37**	<0.05	Supported

Notes: ** denotes a p-value less than 0.05.

Source: Authors' calculation

5. Discussion

5.1 Theoretical implications

Two factors of drones (compatibility and speed) positively impact farmers' desires and anticipated emotion. Risks negatively influence both desire and emotion. These findings also show that farmers' desire and emotions toward drones have pushed their intention to use them. Interestingly, the environmental friendliness of drones plays moderating role in strengthening the relationship between farmer's desire, emotion, and intention. Additionally, surprising results found that drone complexity has no meaningful role in leading farmers' desire and emotions.

The study's findings have several contributions to the literature. Firstly, this research highlights the importance of drone application in agriculture, especially in an emerging economy. Speed is considered the determinant that has the most significant impact on both farmers' desire and emotions. The findings about speed and farmer desire are similar to the suggestions of Lee (2019), Lee and Lee (2020), and Amar *et al.* (2019). They argued that users would desire to use drones if they perceive the speed of drones more than other traditional vehicles. It can be suggested that farmers in developing countries have a strong desire to use drones faster than conventional methods. This finding also explains why farmers in an emerging economy have positive anticipated emotion toward new technology application (Lee *et al.*, 2019). This is in line with the findings of Hamdi *et al.* (2020), which addressed the faster process of drones.

Secondly, this study also highlights the compatibility of drone applications in agriculture. Drone compatibility is found to have a positive impact on farmers' desire and emotion. This is somewhat similar to the research of Tsai and Tiwasing (2021) about the relevance of compatibility to user behaviors and technology adoption (Boateng *et al.*, 2016). Thirdly, complexity is revealed not to impact farmers' desire and emotions significantly. These findings differ from those of previous studies (Yoo *et al.*, 2018; Xu *et al.*, 2020; Xu, 2016).

Fourthly, this study also confirms the negative impact of the risks of drones on farmers' desire and emotions. These findings align with the research of Yi *et al.* (2020), Osakwe *et* *al.* (2022), and Sah *et al.* (2021). Sah *et al.* (2021) demonstrated that being unable to deliver a product can affect the users' emotions. However, these results differ from Miranda *et al.* (2022), which suggests the reliability of drone in reducing the risk of late delivery, lost or damaged goods. In an emerging economy where drones have not yet been applied in any industry, farmers are still afraid of their risks.

Finally, this study highlights the important role of environmental friendliness in transforming farmers' desire and emotion into their intention to use drones. It can be explained that users in an emerging economy care about the environment and tend to use services that are less harmful to the environment (Retamal, 2017; Ngoc *et al.*, 2017). This finding is consistent with prior studies (Soffronoff *et al.*, 2016; Goodchild and Toy, 2018; Lee *et al.*, 2016). Unfortunately, there is currently no research addressing the moderating influence of drone environmental friendliness, which is critical in green research focusing on the attitude-behavior gap. Therefore, this study explores the potential of innovative information technology to mitigate environmental challenges by investigating how environmental friendliness affects the relationships among farmers' desire, emotions, and intentions to use drones in agriculture.

In conclusion, drones have emerged as a pioneering technology in agricultural production. Companies are actively working towards commercializing drones and enhancing their capabilities. While some studies exist on user attitudes and intentions towards drones, this research proposes an integrated model drawing from innovation theory to better understand farmers' perceptions of drones. The empirical results show that compatibility, speed, and risks significantly impact farmers' intention through their desire and emotions.

5.2 Managerial implications

This study has significant managerial implications for stakeholders in agricultural production, including farmers, companies poised to deploy drone applications, and government entities.

Firstly, the study underscores that factors influencing intention can vary based on farmers' motivations and desires. Technology companies should actively collaborate with authorities to integrate mechanization into agricultural practices. This could involve partnerships with the National Agricultural Extension Center to pilot various drone-based agricultural production models. Furthermore, these companies should organize training events to educate pilots on drone operations in agriculture.

Secondly, farmers are encouraged to leverage drone technology to enhance farming efficiency and productivity. They should carefully select drones that best suit their needs, beginning with trials on smaller farming areas before scaling up. Active participation in training sessions is crucial for farmers to gain proficiency in drone utilization.

Thirdly, the government should incentivize farmers to adopt technology in agricultural production, emphasizing the benefits of enhancing productivity through new technologies. This could include facilitating access to credit for innovation and technology adoption in farming. Technical support teams should be deployed to assist farmers to understand the appropriate use of drones. Moreover, the government can provide timely and practical information through training sessions to support farmers effectively.

6. Conclusions

This research identifies key factors influencing farmers' intention to use drones: compatibility, complexity, and speed. Drones in agriculture enable efficient data collection, saving farmers time and effort compared to traditional methods. This capability enhances decision-making in irrigation, fertilization, pesticide application, and livestock management, thereby improving agricultural productivity and product quality. These findings provide insights for government and policymakers aiming to encourage drone adoption in agriculture.

However, this study has several limitations. Firstly, it focuses only on these three determinants of drones, while other studies have identified additional factors influencing farmers' intentions. Future research should explore these factors, such as risks and compatibility. Secondly, the study measures dependent variables assuming that drone adoption in agriculture is still emerging, without reflecting changes in agricultural production after widespread drone adoption. Future studies could use longitudinal data to investigate the dynamic impact of drone factors on farmers' intentions over time. Lastly, the study was conducted in Northern Vietnam. Future research could expand to other provinces in Southern Vietnam, such as Binh Phuoc, Hau Giang, and Long An, to broaden the geographical scope and generalize findings.

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