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ARTICLE

The Effect of Farm Size on the Decision to Adopt Digital Technology: The Case of Unmanned Aerial Vehicles in Rice Production in Vietnam

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ABSTRACT

Agricultural production efficiency depends heavily on the decisions of the household head or member directly growing rice, especially the decision related to the adoption of digital technology, because this is the main tool to reduce costs, improve crop yield and environmental quality. Despite the potential, there are still some operational limitations that require comprehensive development of features and human resources to effectively apply the technology. In this paper, the adoption of digital technology in rice production has provided numerous practical benefits for households. However, the adoption rate of digital technology features, particularly unmanned aerial vehicles (UAVs), remains low in most developing countries. This study aims to determine the impact of farm size on the decision to adopt UAVs in rice production among households in the Mekong Delta, Vietnam. The research utilizes

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primary data collected through direct interviews with 940 households that have applied or plan to apply UAVs in their rice cultivation process. The results indicate that most households have adopted UAVs for three key activities: seeding, fertilization, and pesticide spraying. Additionally, the estimation results reveal a nonlinear, inverted U-shaped relationship between farm size and the decision to adopt UAVs in rice production. Furthermore, the study identifies other factors, aside from farm size, that influence the decision to use UAVs in rice production among Vietnamese households.

Keywords: Digital Technology; Farm Size; Households; Rice Production; Unmanned Aerial Vehicles

1. Introduction

The Green Revolution of the 21st century has marked a significant turning point in the usage of new technologies in farming production. The main objective is to improve productivity, thereby contributing to poverty reduction among farming households. Among the applied technologies, information and communication technology (ICT) has emerged as a promising field, incorporating tools such as big data, cloud computing, and artificial intelligence. In 2014, the Massachusetts Institute of Technology identified unmanned aerial vehicles (UAVs) in agriculture as one of the most notable green technologies, promoting smart agriculture [1]. UAVs not only support field monitoring but also provide crucial information for making optimal farming decisions [2]. The increasing adoption of UAVs has been delivering tangible benefits to households.

In Vietnam, rapid rural-to-urban migration has led to a severe labor shortage in agriculture. Agricultural mechanization has become an inevitable trend to address this issue. Currently, mechanization efforts primarily focus on applying machinery and equipment in planting and harvesting. Additionally, automation in agricultural production through other technologies, including UAVs and drip irrigation systems, continues to show great potential in Vietnam. Despite still being in its early stages compared to more developed agricultural economies, these technologies promise significant benefits. The application of UAVs in agriculture is becoming increasingly important. UAVs have played a crucial role in recent years in agricultural crop production [3]. Furthermore, the ongoing development of UAV technology is expected to expand its applications in smart agriculture.

Deploying UAVs for crop monitoring can significantly increase crop productivity while effectively preventing pest infestations [4]. UAVs can be equipped with cameras and sensors to capture images and collect data on crop conditions, helping households detect problems early and implement timely interventions. Moreover, UAVs play a vital role in optimizing households' time by participating in activities such as soil fertilization, pesticide spraying, irrigation, crop health assessment, planting, and livestock monitoring [5]. This significantly reduces the workload for both households and operators. UAVs demonstrate the ability to operate on wet and sloped surfaces, applying precise treatments to targeted areas. They can take off and land vertically while maintaining efficiency at low altitudes. Real-time farm data provided by UAVs enables households to make well-informed decisions regarding agricultural inputs.

According to Boursianis et al. [6], UAVs play a crucial role in smart agriculture by analyzing their applications in various situations, including irrigation, fertilization, pesticide use, weed management, crop growth monitoring, disease management, and field-level phenotypic analysis. Furthermore, the use of UAV systems in complex agricultural environments has also been analyzed. However, despite being the technological advancement for a long period, the adoption of UAVs among farming households in the Mekong Delta, Vietnam, remains relatively limited. The primary functions used by households are sowing, fertilizing, and pesticide spraying due to their practical benefits. However, other digital functions of UAVs, such as data collection, monitoring, and crop health assessment, are less utilized due to weather dependency [7,8] and the high cost of UAV usage compared to traditional spraying machines [9].

In addition, the area of production land is considered the first factor and plays an important role in the process of applying digital technology [10–13]. However, at different stages of the economy, the scale of production land of the household has different effects on digital technology. First, scholars [14,15] found a negative relationship between the size of the household's land and the application of digital technology. On the contrary, Nguyen et al. [13] argued that farmers with larger production land areas are more likely to apply digital technology, typically UAVs, to rice production than farmers with small production land areas because they can dedicate part of their land to test new technology, if successful, they will fully apply the technology to their farming and actively invest in various types of digital technology [12,16–20]. Based on that, it shows that land area has a two-way influence on the decision to apply digital technology. Therefore, this study was conducted to fill the gap of previous studies by investigating the nonlinear relationship between the land size and the decision to apply digital technology, typically UAVs.

Simultaneously, to promote UAVs adoption in farming, Vietnam in general, and the Mekong Delta in particular, are aligning with the recently developed technology trend. However, the application of digital technology in agricultural production remains limited due to several factors, including low technology adoption rates (with only 45% of the Mekong Delta's agricultural land using digital technology for sowing, fertilizing, and pesticide spraying) [21], underdeveloped technical infrastructure, and small-scale farming. This study aims to identify the key factors influencing households' decisions to adopt digital technology in cultivating rice in the Delta of Mekong area. From these findings, the paper proposes suitable solutions to encourage households to integrate digital technology into their production practices.

We begin this paper by presenting the theoretical framework and research model, followed by the research methodology. Next, we present the research findings, and finally, we conclude with recommendations to scale up the adoption of digital technology in rice production among studied households.

2. Theoretical Basis

2.1. Concept

Numerous studies have proposed different definitions of digital agriculture or digitalization in agriculture [22–25]. Most of these studies refer to digital technologies such as the Internet of Things (IoT), cloud computing, big data, blockchain, artificial intelligence (AI), robotics, and unmanned aerial vehicles (UAVs) in agricultural production. These technologies are widely applied throughout the production process—from the input stage (field mechanization, automated irrigation systems, UAVs for data collection or for sowing, fertilizing, and pesticide applying, the systems of greenhouse, etc.) to the outcome stage (gathering information about the market, connecting the enterprises to reduce the value disparities by bypassing intermediaries, etc.).

According to Nguyen et al. [13], an unmanned aerial vehicle is an aircraft that can fly along a pre-set route with the help of an autonomous system and GPS coordinates. The device also has conventional radio control; it can be controlled manually in case of failure or dangerous situations. Sometimes the term UAVs is used to refer to the entire system, including the ground station and video system, however the term is often used for model airplanes and helicopters with both fixed and rotary wings [26,27].

2.2. The Influence of Land Size and Other Factors on the Decision to Apply Digital Technology in Rice Cultivation

The applying of digital technology helps farming households lower the costs of input, strengthen the productivity, as well as improve the efficiency of the economy. For example, unmanned aerial vehicles (UAVs) can be used to collect data on crop conditions, enabling farmers to make precise decisions regarding the amount of fertilizer and pesticides to apply, thereby saving costs and minimizing environmental impacts. In this study, digital technology – specifically UAVs – is examined in the context of rice farming households using them for sowing, fertilizing, and pesticide spraying. The use of UAVs in rice cultivation not only reduces the labor burden on farmers but also increases crop yields due to their high precision. Moreover, UAVs help reduce the risk of farmers being exposed to hazardous chemicals. However, the adoption of UAVs in rice farming also faces several challenges. High initial investment costs, along with expenses for maintenance, repair, and upgrades, make ownership difficult for many small-scale farmers, especially those living in remote areas where access to technical support is limited. Additionally, operating UAVs requires specialized knowledge and skills that many farmers currently lack. UAVs also have limited payload capacity and short flight times, requiring frequent battery changes, which may reduce their efficiency on large-scale fields. Due to these limitations, most farming households is unable to invest in UAVs ownership but rely primarily on rental services instead. Therefore, this study aims to explore the factors influencing the decision to adopt UAVs in rice cultivation among farming households in the Mekong Delta.

One of the key factors influencing the decision of farming households to adopt UAVs in rice production is ***farm size***[10,12,13,28,29]. Households with small landholdings often rely on family labor or hire external labor to carry out production activities. Moreover, land fragmentation may reduce the motivation to adopt digital technologies[30]. In contrast, larger landholdings have a direct and positive effect, encouraging households to adopt digital technologies in production[12,13,17–20,31]. This is because households with extensive farmland typically face challenges in managing all farming tasks using only family labor, making them more likely to invest in digital technology solutions[16]. Furthermore, although these households may have stronger financial capacity, they often face time constraints, which further motivates them to adopt digital technologies to optimize production processes[12,32,33]. For these reasons, this study expects that farming households with larger landholdings are more likely to accept and adopt UAVs in rice production compared to those with smaller plots.

Income is one of the key factors influencing farmers' decisions to adopt digital technologies[34], especially in the context of rural credit markets that remain underdeveloped[35,36]. As income increases, farming households are more capable of investing in new technologies, thereby reducing their reliance on external borrowing. Higher income not only helps overcome financial barriers but also motivates farmers to scale up production and pursue agricultural industrialization[36,37]. Numerous experimental studies have demonstrated a positive relationship between income and the adoption of digital technologies in agricultural production[17,18,20,38]. However, some studies have also reported a negative impact of income, suggesting that this relationship may be complex and context-dependent, influenced by factors such as investment motivation, access to technology, and farmers' awareness[17]. Overall, the evidence suggests that income tends to promote the adoption of digital technologies, although the degree of influence may vary depending on the socio-economic conditions and regional characteristics of different farming households.

Education is recognized as a foundational factor that plays a catalytic role in facilitating access to and effective utilization of new technologies. Numerous academic studies have emphasized the importance of educational attainment as a key determinant of the ability to adopt technological innovations[31,39–42]. Notably, studies by Gebrehiwot & DerVeen[43], Addisu et al.[44], Mao et al.[45], Dung et al.[12], Fadina & Barjolle[33], Kaliba et al.[46], Zhou et al.[47], Cai et al.[18], and Liu et al.[20] have demonstrated a statistically significant positive correlation between farmers' educational levels and their likelihood of adopting technology. This relationship is particularly pronounced with advanced technologies, which often require users to possess certain levels of knowledge and skills to operate and apply them effectively[18,20,47]. This implies that higher education can equip farmers with the ability to absorb information, assess benefits, and overcome technical barriers associated with the adoption of digital technologies in agricultural production.

Access to credit is considered a key factor in promoting the adoption of technology in agricultural production among farmers[18,48]. Many studies have shown that when farmers have access to loan capital, they are more likely to invest in new technologies-even those with higher risks-thanks to reduced financial pressure and an increased capacity to take on risk[49]. Credit enables farmers to make more proactive decisions, minimize investment risks, and focus on modern farming solutions that yield higher efficiency[48]. Based on this, policymakers should prioritize improving rural credit systems to facilitate timely and appropriate access to financial resources for farmers, enabling them to invest in digital technologies for production. However, access to credit does not always guarantee the successful adoption of technology. Some studies have pointed out that even when credit is available, farmers still face many obstacles in implementing technological innovations due to factors such as legal barriers, strict lending conditions, or high initial investment requirements [43,44,50,51]. These challenges highlight the need for a more comprehensive credit policy—one that goes beyond merely providing capital and is integrated with technical support, training, and institutional reform to effectively promote technology adoption in agriculture.

The ***age*** of the household head is an important demographic variable and is identified as a potential determinant influencing the adoption of digital technologies in the agricultural context [15,16]. However, the relationship between age and technology adoption remains inconclusive in current studies [17,18,47]. Some studies suggest that age is negatively correlated with the tendency to apply recently developed technologies [13]. This matter is often clarified by the evidence that younger farmers tend to possess a more long-term visual perception with a higher degree of technological orientation [52]. In contrast, older farmers may face various barriers - physical (health-related), cognitive (limited knowledge), or psychological (resistance to change) - which can hinder their ability to access and use new technologies. In summary, the age of the household head is a multifaceted factor that may exert a complex influence on the decision to adopt digital technologies in agriculture.

Similar to age, the role of ***gender*** in agricultural production and the adoption of digital technologies is a topic that has attracted considerable attention and debate. Empirical studies have provided mixed evidence regarding the impact of gender on the adoption of digital technologies in this field. Some perspectives suggest that women tend to be less likely than men to adopt new technologies [13,53]. This may stem from traditional gender roles in households, where women are often responsible for domestic tasks and caregiving, resulting in limited direct involvement in agricultural production activities. Moreover, women may face more barriers in accessing employment opportunities, and even when they participate in production, they often encounter constraints in terms of resources, access to information, and training related to new technologies. In addition, social and cultural factors can limit women's participation in decision-making processes regarding technology adoption. Gender differences may also reflect differing preferences or priorities regarding recently developed agricultural technologies. However, experimental studies on the adoption of digital technologies in maize production in Ghana [14], coffee production in Papua New Guinea [54], and rice production in Viet Nam [13] found no significant effect of gender on adoption decisions. In contrast, studies by Wachenheim et al. [17], Zheng et al. [38], and Cai et al. [18] reported significant gender-based differences, with men being more likely than women to adopt digital technologies. These contrasting findings suggest that the relationship between gender and digital technology adoption in agriculture is complex and may be influenced by various context-specific factors.

The size of a household's ***labor force*** can influence the decision to adopt digital technologies in agricultural production through various mechanisms. On one hand, households with abundant labor may have more opportunities to access and exchange information about digital technologies, thereby increasing their understanding and reducing the risks associated with adoption [51,55]. Particularly in the context of agricultural mechanization, which still requires human involvement in certain stages, a larger family labor force can facilitate the implementation of such technologies. On the other hand, the availability of family labor may affect the motivation to adopt technology in the opposite direction. Danso-Abbeam et al. [56] and Kaliba et al. [46] emphasize situations where work is scarce and the cost of hiring external labor is high, adopting technology becomes essential to compensate for labor shortages. Conversely, if the household has abundant family labor with low opportunity costs (e.g., limited access to off-farm employment), the household may prioritize using existing labor over investing in capital-intensive technologies. Nonetheless, a larger household size, which implies a higher potential labor pool, may offer advantages such as reduced need for hired labor and increased access to other resources [13]. Additionally, family members can share knowledge and experiences related to technology, creating a supportive environment for learning and adopting new digital solutions. Therefore, the overall impact of household labor size on digital technology adoption is complex and depends on the interaction of various economic and social factors.

Conversely, the empirical study by Asrat and Simane [51] in the Dabus River Basin, Northwestern Ethiopia, revealed an interesting correlation: the greater the ***geographic distance*** between the residence and the rice field, the more likely farmers are to adopt digital technologies. A plausible explanation for this phenomenon is that transaction and transportation costs, including both labor and agricultural inputs increase significantly with longer travel distances. In such contexts, digital technologies have the potential to mitigate these difficulties and reduce losses, particularly in crop protection and maintain rice productivity. Furthermore, a key driver behind farmers' adoption of new technologies is their awareness of the tangible benefits these technologies can offer [57–62]. The study by Brown and Roper [59] on agricultural technology adoption in New Zealand demonstrated that the effective demonstration of new technologies within farmer networks has a significant influence on others' decisions to adopt similar innovations. This highlights the crucial role of technology transfer and the importance of building trust through concrete evidence of successful implementation.

Households tend to adopt new technologies when they recognize tangible benefits [57–62]. Brown & Roper [58] studied technology adoption in the New Zealand agriculture and found that real-world demonstrations of new technologies within household networks encouraged widespread adoption. ***Technical training*** serves as a channel for transmitting knowledge and experience, facilitating information exchange among farmers and strengthening their confidence in the potential of new technologies [13]. Through well-structured training programs, farmers can acquire specialized knowledge, gain a clearer understanding of the economic benefits offered by new technologies, overcome the fear of change, and shorten the time needed to master the technology [30,45]. In addition, technology demonstration activities provide farmers with hands-on opportunities to experience and objectively assess the advantages of new technologies. This direct interaction has a strong motivational impact, as tangible, proven benefits are often more convincing than theoretical information.

Farming experience is widely recognized as a key factor reflecting the technical skill level of farmers [40,59,63]. The study by Paustian and Theuvsen [63] found households that have extensive knowledge in producing farming products tend to be more proactive in adopting new technologies. This can be explained by the fact that accumulated experience provides farmers with a solid foundation of knowing, practical experience, as well as a thoughtfulness of perfect cultivation procedures. As a result, experienced farmers are better equipped to accurately assess the potential and benefits of new technologies based on past lessons and hands-on insights. This capacity for informed decision-making, grounded in strong experiential knowledge, plays a crucial role in promoting the adoption of technology in agricultural production.

Moreover, the study by Wachenheim et al. [17], based on previous studies, emphasized that resource endowment plays a vital role in the decision to adopt digital technologies in agriculture. The concept of “resource endowment” here encompasses both internal resources and capacities of the farmers and their families, as well as external factors such as ***geographic location, relationships with local authorities, participation in cooperatives, and household income levels***. These factors can either create advantages or pose barriers in terms of accessing information, capital, skills, and necessary support for adopting digital technologies.

Based on theoretical frameworks and empirical findings from rice farming in the Mekong Delta, Vietnam, the proposed empirical model is as follow:

$$AdopDigTech_{ij} = \beta_0 + \beta_1 Farmsize_{ij} + \beta_2 Farmsizesq_{ij} + \beta_3 Labor_{ij} + \beta_4 Age_{ij} + \beta_5 Female_{ij} + \beta_6 Education_{ij} + \beta_7 AccessCredit_{ij} + \beta_8 Training_{ij} + \beta_9 Experience_{ij} + \beta_{10} Residence_{ij} + \beta_{11} Ethnicity_{ij} + \beta_{12} Distance_{ij} + \beta_{13} IncomeRation_{ij} + \beta_{14} LocalAuthorities_{ij} + \beta_{15} Cooperative_{ij} +$$

$\beta_{16}Income_{ij} + \beta_{17}Angiang_{ij} + \beta_{18}Haugiang_{ij} + \beta_{19}Kiengiang_{ij} + \beta_{20}WinterSpring_{ij} + \varepsilon_i$

where $AdopDigTech_{ij}$ is the dependent variable, which takes the value 1 if the i-th household in the j-th season adopts recently developed technology in rice cultivation, and 0 otherwise.

3. Research Methodology

3.1. Data Collection

This study conducted interviews with key subjects, specifically rice-producing families in four provinces of the Mekong Delta area, Vietnam. These provinces were selected as the representatives of a broader population, covering provinces of highland in the west (An Giang and Can Tho) and those of lowland coast in the east (Hau Giang and Kien Giang). The sample was selected based on the amount of rice-cultivating land in each province, according to the 2023 Statistical Yearbook. Specifically, direct interviews were conducted with 332 rice households in An Giang (representing 35.32% of the total cultivated land in the studied Mekong Delta provinces), 384 households in Kien Giang (40.85%), 120 households in Can Tho (12.77%), and 104 families in Hau Giang (11.06%). Data collection took place from May 2024 to August 2024.

The sample was randomly selected based on the list provided by the local authorities to ensure an accurate reflection of the actual agricultural production situation. The study was conducted in two phases including preliminary interviews and formal interviews.

First, a pilot survey with 5–7 households was conducted to refine and complete the questionnaire with the following research questions:

(1) What is the current status of digital technology application in rice production of households in the Mekong Delta?

(2) What factors influence the decision to apply digital technology in rice production of households in the Mekong Delta?

(3) What recommendations are proposed to attract households to apply digital technology in rice production across the region?

In the second stage, formal interviews were conducted with 940 household heads (or household members directly involved in rice production) across the study area. These households included those who have adopted, are currently adopting, or plan to adopt UAVs technology in their rice production. Interviews were conducted using a structured questionnaire and covered two cropping seasons: Winter-Spring and Summer-Autumn 2024.

The collected information included household demographics, production conditions, investing costs into farming activities (land preparation, irrigation, seeds, fertilizers, pesticides, labor, harvesting, machinery depreciation, credit, etc.), production controlling methods, land characteristics, access to credit sources, and, most importantly, the types of digital technologies that households have used, are using, or plan to use in production. The study also examined the advantages and challenges of digital technology adoption, as well as households' perspectives on how digital technology can be optimized to enhance efficiency. These insights serve as a foundation for proposing effective digital technology solutions and expanding the adoption of such models in rice farming.

Through field findings, it was observed that recently developed technology adoption is becoming increasingly common in recent years. Among these technologies, unmanned aerial vehicles were the earliest to be adopted by households for rice cultivation. The primary reason for this early adoption is that UAVs help reduce manual labor, enhance operational efficiency, minimize crop trampling, and improve overall productivity. Therefore, the main form of digital technology surveyed in this study was UAVs used for seeding, fertilization, and pesticide spraying. Other forms of digital technology have yet to be widely adopted due to various challenges such as the shortage of knowledge of technology, financial difficulties, and small-scale farming operations.

3.2. Analytical Method

The Probit regression method was used to predict the elements influencing farming households' decisions to use digital technology in rice production. The dependent variable, which represents the willingness to use, is binary (either willingness to use it or not). Therefore, the Probit model is employed to reckon the household's decision-making behavior regarding the use UAVs [13,17,64], as expressed in the following equation:

$$y_i^* = X_i\beta + \mu_i$$

$$Pr\left(y_i = 1|X_i\right) = Pr\left(y_i^* > 0|X_i\right) = Pr\left(\mu_i \geq -X_i\beta|X_i\right) = \varphi\left(X_i\beta\right)$$

where y_i represents the correspondent of digital technology adoption in rice farming by families, y_i^* is a latent variable that reveals y_i and equals 1 if its value is ≥0. X_i is the vector of all independent variables, which are separated into seven independent variables which are detailed in the theoretical framework and empirical model section on the elements that affect the decision to adopt recently developed technology in rice production by farming families in the Mekong Delta area.

The study employs descriptive statistical methods to provide an overview of the characteristics of farming households and their adoption of digital technology in rice production. Additionally, the Probit regression method is used to determine the extent and influence of various factors on the decision to adopt recently developed technology in rice production with the following reasons: (1) the dependent variable analysis is binary (0–1) based on a cross-sectional dataset of 940 observations of rice-growing households, in which the dependent variable reflects the decision of the household to adopt or not to use UAVs in rice production. The model assumes that this decision is formed from a latent variable that follows a normal distribution. (2) Compared to the Logit model, the Probit model has the advantage of being more suitable when assuming a reasonable normal distribution of the error, and at the same time is less sensitive to outliers because the normal distribution function has a shorter tail than the logistic function [65]. Another advantage is that the relatively large sample size (940 observations) helps the distribution of the latent variable and the error approach a normal distribution, thereby increasing the reliability and stability of the Probit estimate. In addition, Probit is often used in econometric studies related to binary choice decisions, credit, finance, etc. because of its ability to closely align with the latent variable theoretical framework [66]. (3) The panel data model is not applied because the data set is only cross-sectional, does not follow the same household over many points in time, so it does not satisfy the basic conditions for applying panel data analysis [67]. Data analysis is conducted using Stata 15.0 software.

4. Results and Discussion

4.1. Characteristics of Households and the Adoption of Recently Developed Technology in Rice Production

Based on interviews with 940 rice farming households (**Table 1**) that have adopted, are adopting, or plan to adopt digital technology in various stages of rice cultivation, the findings indicate that rice farming has been practiced for a long time applying the inherited knowledge. This has led to a generally low educational level among households. Approximately 70% of households in the surveyed group have an almost low coordination of education (grade 7 on average). This reason is partially because they grew up during a period when Vietnam had just emerged from war (with an average age of 51), and economic hardships limited their opportunities for formal education. Additionally, the strong attachment to their farmland means that households have little need to travel far, with a mean distance from home to their fields being almost about 1.62 km. Moreover, the average household income remains relatively low (178.42 million VND per year). As a result, most farming households have chosen to adopt digital technology in the form of UAVs to assist with tasks such as seed broadcasting, fertilization, and pesticide application. Other kinds of recently developed technology have not been widely adopted because of financial constraints, soil conditions, operational and maintenance challenges, and other limitations.

Despite having extensive farming experience (an average of 27.4 years), household income remains modest. The primary reason is the small-scale nature of farming operations, with an average landholding of only 1.83 hectares per household. While experience enables households to optimize production within existing conditions, integrating digital technology is crucial for improving efficiency and increasing income. Furthermore, with an average of only 1.32 laborers per household, ensuring timely and high-quality rice production presents significant challenges. Thus, the adoption of recently developed technology both enhances productivity and helps address labor shortages in agriculture.

Table 1. Characteristics of Rice Farming Households.

Criteria	Unit	Average	Standard Deviation	Minimum	Maximum
Family members	People	3.99	1.21	1.00	8.00
Household labor	People	2.77	0.90	1.00	5.00
Household labor in rice farming	People	1.32	0.51	1.00	3.00
Household head's age	Years	50.88	10.91	26.00	79.00
Education level	Years of schooling	7.43	3.75	0.00	16.00
Rice farming experience	Years	27.37	12.29	1.00	60.00
Length of residence	Years	47.26	12.13	1.00	79.00
Rice farming area	Ha	1.86	2.02	0.20	20.00
Total income	Million VND/year	178.42	151.08	10.00	1500.00
Income from rice	Million VND/year	125.65	97.55	10.00	825.00
Distance to field	Km	1.62	3.66	0.00	60.00

Descriptive statistics in **Table 2** display a firm trend, with 59.36% of farming families having adopted recently developed technology in rice production processes including seed broadcasting, fertilization, as well as pesticide spraying. This indicates that households are beginning to embrace digital technology, although adoption rates remain relatively low. A key reason for this may be the lack of information about these technologies, as only 40.21% of families have joined training courses embodied by technology providers. These training sessions play a crucial role in raising awareness about different types of recently developed technology, their techniques, and the advantages they bring to these families. Additionally, approaching capital (both officially and unofficially) remains highly limited due to various barriers and complex loan procedures. Conventional paddy farming is often connected with physically demanding labor, which explains why most farm workers are males. The study indicates that 94.26% of the primary labor force in rice farming households is male. The survey also confirms that the vast majority of respondents belong to the Kinh ethnic group, which aligns with Vietnam's demographic reality, as the Kinh people form the majority of the population. Furthermore, most rice farming households have little participation in cooperative or local government positions, as rice farming has traditionally been passed down through generations. However, in recent years, some households with university-educated members have begun participating in local governance.

Table 2. Support Activities in Rice production of Farming Households.

Criteria		Number of Families	Percentage (%)
Adoption of digital technology	Yes	558	59.36
	No	382	40.64
Taking part in digital technology education	Yes	378	40.21
	No	562	59.79
Access to credit	Yes	74	7.87
	No	866	92.13
Gender of household head	Female	54	5.74
	Male	886	94.26
Ethnicity	Kinh	926	98.51
	Other	14	1.49
Family member as a local official	Yes	97	10.32
	No	843	89.68
Participation in cooperatives	Yes	26	2.77
	No	914	97.23

4.2. Estimation Results of Elements Influencing the Designation to Adopt Recently Developed Technology in Rice Production by Households in the Mekong Delta Region, Viet Nam

Before presenting the research findings, the data in this study were tested for multicollinearity and heteroscedasticity. The findings indicate that there is not any presence of multicollinearity or heteroscedasticity. Therefore, the results presented in **Table 3** are considered reliable.

Table 3. Estimation Results of Elements Influencing the Designation to Adopt Recently Developed Technology in Rice Production.

Variable	Description	Coef	Stad. Err.	P-Value
Farmsize	Rice farming farm size	0.0869***	0.0312	0.005
Farmsizesq	Squared farm size	–0.0043*	0.0025	0.090
Labor	Labor size	–0.0074	0.0691	0.915
Age	Household head's age	–0.0170**	0.0077	0.030
Female	= 1 if household head is female, = 0 otherwise	–0.0287	0.2406	0.905
Education	Education level	0.1350***	0.0171	0.000
AccessCredit	Access to credit	0.2255	0.2281	0.323
Training	Participation in digital technology training	0.8183***	0.1225	0.000
Experience	Rice farming experience	0.0020	0.0070	0.773
Residence	Duration of residence	0.0087	0.0068	0.200
Ethnicity	= 1 if household head is Kinh ethnic group, = 0 otherwise	0.7088*	0.3889	0.068
Distance	Distance from home to rice field	0.1672***	0.0366	0.000
IncomeRatio	Ratio of rice income to total household income	–0.0011	0.0027	0.698
LocalAuthorities	= 1 if a family member is a local official, = 0 otherwise	0.7212***	0.1955	0.000
Cooperative	= 1 if the household is a member of a cooperative, = 0 otherwise	0.3324	0.3685	0.367
Income	Household rice income	0.0040***	0.0008	0.000
Angiang	= 1 if the household is in An Giang, = 0 otherwise	0.9857***	0.1753	0.000
Haugiang	= 1 if the household is in Hau Giang, = 0 otherwise	–1.1465***	0.3541	0.001
Kiengiang	= 1 if the household is in Kien Giang, = 0 otherwise	1.6114***	0.1910	0.000
WinterSpring	= 1 if farming in the Winter-Spring season, = 0 otherwise	–0.0168	0.1100	0.879
Cons	Constant	–3.0628***	0.5685	0.000
Number of observations		940		
Prob > chi2		0.0000		
Pseudo R2		0.4731		
Log likelihood		–334.59043		

Notes: *, **, *** represent significance levels of 10%, 5% and 1%. Dependent variable: = 1 if the household adopts digital technology in rice production, = 0 otherwise.

The estimation results show that the regression model is highly statistically significant and has identified a nonlinear inverted U-shaped (∩) relationship between farm size and the decision to adopt digital technology in rice production. Additionally, nine factors were found to positively influence the adoption of digital technology in household rice farming, including farm size, household income from rice farming, education level, participation in training programs, distance

from home to rice fields, having a family member as a local official, ethnic differences, and regional differences in An Giang and Kien Giang. Conversely, squared farm size, the age of the household head, and regional differences in Hau Giang have a negative relationship with the adoption of this technology.

First, the regression results indicate a nonlinear ∩-shaped relationship between farm size and the decision to adopt digital technology for rice farming, with a high statistical significance level of 1% for the farm size variable and 10% for the squared farm size variable. This suggests that as farm size expands, households are more likely to access information and confidently adopt digital technology in rice production due to its convenience and efficiency [13], as previously discussed, as well as the advantages of scale. Wachenheim et al. [17] offered two key reasons supporting this initial positive relationship. First, expanding land area facilitates economies of scale in the learning and use of technologies such as UAVs. Second, adopting digital technology may yield higher economic returns on larger scales due to the ability to negotiate discounts or favorable rental terms. This result is consistent with empirical studies conducted in Dera Wearda, South Gondar, Ethiopia [32]; Zou Province, South Benin [33]; Jilin Province, China [17]; and Mekong Delta, Viet Nam [13]. However, when farm size exceeds the optimal threshold, further expansion becomes burdensome for households due to several constraints: limited managerial capacity, as the household head's education level is only around grade 7; financial constraints; and a shortage of specialized labor to operate digital technology. These factors negatively affect the efficiency and benefits derived from the adoption of digital technology.

Furthermore, households with higher income from rice farming are more likely to access digital technology. With better financial capacity, they are more willing to invest in new technologies for rice production. The estimation results show that the variable representing income from rice farming has a positive coefficient with a 1% significance level, which indicates that families with higher incomes are more inclined to adopt digital technology compared to those with lower income. This finding is also supported by studies conducted by Cai et al. [18] and Liu et al. [20] in China.

Education level and participation in technical training programs also have positive coefficients at a 1% significance level. Households with higher education tend to have broader understanding of production procedure and the challenges they face. As a result, they are able to judge and select recently developed technologies which are coordinating with their farming conditions. Corresponding, families that take part in technical courses or attend recently developed technology shows are more likely to adopt recently developed technology in paddy farming. The finding is along with the theoretical framework and aligns with research findings from Zhou et al. [39] and Cai et al. [18].

The geographical distance between home and rice fields also has a positive and highly statistically significant coefficient at the 1% level, indicating that households with rice fields farther from their homes are more likely to adopt digital technology. This is because long travel distances make commuting difficult, encouraging households to complete their work as quickly and efficiently as possible. Therefore, applying digital technology in rice farming has become essential. Studies by Addisu et al. [44], Asrat and Simane [51] also suggest that households with fields located farther from their homes are more likely to adopt new technologies.

Regional differences in An Giang and Kien Giang, as well as ethnic differences, also positively influence the decision to adopt digital technology. The results suggest that households in An Giang and Kien Giang are more likely to adopt digital technology compared to those in Can Tho. Similarly, ethnic Kinh household heads are more likely to adopt digital technology than those from other ethnic groups.

As expected, the variable representing households with a family member working as a local official has a positive coefficient at a 1% significance level. This finding is consistent with expectations, as households with relatives in local government typically have quicker access to information on technology and related support policies, particularly financial assistance. In the context where farmers are often cautious and risk-averse, having someone knowledgeable about policy systems provides reassurance and encourages them to adopt new technologies [17].

Conversely, households in Hau Giang have a negative relationship with the decision to adopt digital technology at a 1% significance level. This result implies that rice-farming households in Hau Giang are less likely to adopt digital technology than those in Can Tho, as they perceive digital technology investment to be more expensive compared to traditional methods. Similarly, older household heads are less likely to adopt digital technology due to conservative attitudes and the belief in traditional farming practices being passed down through generations.

Cooperative membership did not have a significant effect. This result is consistent with the practical context in the Mekong Delta, where most agricultural cooperatives still focus on traditional services such as providing inputs, purchasing rice, and providing credit, while modern mechanization services, especially UAVs, are very limited [68,69]. The decision to adopt UAVs by households in the study area may be more influenced by individual factors (income, land size, perceived benefits) and access to external services, rather than by cooperative membership. This reflects the observation of Nguyen and Tran [69] that "the decision to adopt new technologies in rice production in the Mekong Delta is still mainly based on the capabilities and needs of each household, rather than being a direct consequence of participating in collective production organizations." At the same time, this estimation result is also completely consistent with the research practice of Wachenheim et al.[17] in Jilin province, China.

Additionally, factors such as the number of household laborers in rice farming, access to credit, gender differences of household heads, rice farming experience, length of residence in the area, income ratio, and seasonal differences in the Winter-Spring crop do not show statistically significant coefficients. Therefore, this study cannot determine whether these factors influence households' decisions to adopt digital technology.

5. Conclusion and Recommendations

The study primarily utilizes primary data collected through direct interviews of 940 paddy farmers who have applied recently developed technology in rice production during the Winter-Spring and Summer-Autumn seasons in four provinces of the Mekong Delta, Vietnam, in August 2024. The survey data were obtained using a structured questionnaire and a random sampling method, with the interview distribution based on the amount of paddy-planting land area of each province relative to the Mekong Delta region. Additionally, using the Probit regression estimation method, the study found that the model is statistically significant. The research identifies several factors that positively influence households' decisions to adopt digital technology in rice production, including farm size, household income from rice farming, education level, participation in technical training, distance from the household to the rice field, ethnic differences, regional differences (in An Giang and Kien Giang), and family members who are local officials. On the other hand, factors that hinder the designation to adopt recently developed technology in rice production include the age of the household head and regional differences in Hau Giang. Furthermore, the study confirms a nonlinear inverse U-shaped relationship between farm size and the decision to adopt digital technology in rice production. This suggests that digital technology is not only adopted by large-scale households but also by some small-scale farmers with strong organizational capacity or effective participation in production linkages.

Thanks to the analysis results, the study recommends several recommendations to promote the application of recently developed technology in rice production:

Strengthening the dissemination of knowledge and skills in digital technology. The government should regularly organize workshops, training sessions, and real-world demonstration models of use UAVs in rice farming. These activities allow farmers to directly observe, learn, and assess the feasibility of technologies before adopting them.

Encourage collective production models. For households with small and fragmented landholdings, participating in cooperative models such as "large-scale fields," agricultural cooperatives, or farmer groups will help them access UAVs more easily through economies of scale and shared investment costs.

Targeted financial support policies. Preferential credit programs or subsidies for UAVs equipment should prioritize households with high adoption potential-particularly younger farmers, those with higher education, and those who actively engage with markets.

Localized support policies based on regional characteristics. As significant differences exist between provinces, policies promoting use UAVs should be flexible and tailored to the socioeconomic conditions and behavioral tendencies of farmers in each specific region.

Although this study provides important findings on the influence of land size and other factors on the decision to adopt UAVs in rice production in the Mekong Delta, there are some limitations that should be noted. First, the study used cross-sectional data collected in 2024, thus reflecting the relationship only at a certain point in time and does not allow for analysis of changes in farm households' UAV adoption behavior over time. Second, the research model does not include some important latent variables that may influence the decision to adopt UAVs, such as the level of access to market information, the quality of local UAV services, the farmer's social network, or specific support policies from local authorities. Third, the survey sample was limited to four provinces in the Mekong Delta (An Giang, Kien Giang, Hau Giang, Can Tho), so the results may not fully reflect the diversity of natural conditions, socio-economic conditions, and mechanization levels of other rice-growing regions in Vietnam. Finally, the study focused on analyzing the application of UAVs in three main stages (seeding, fertilizing, and spraying) and did not comprehensively evaluate advanced applications such as data collection, crop growth monitoring, or image analysis, which could bring long-term benefits to rice production management. Therefore, further studies are needed to fill this research gap in the future.

Author Contributions

D.L.N. contributed to conceptualization, methodology, validation, formal analysis, investigation, data curation, writing—preparation of original draft and writing, review, editing, supervision and correspondence. H.V.C. contributed to conceptualization, methodology, validation, formal analysis, investigation, data curation, writing—preparation of original draft and writing, review, editing, supervision. N.A.T.N. contributed to literature review and writing. V.T.T.D. contributed to formal analysis, investigation, and data curation. T.H.N. contributed to validation, literature review. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

This study did not involve human participants, animal subjects, or any clinical trials requiring ethical approval. Therefore, ethical approval was not required. For survey-based research, informed consent was obtained from all participating farmers before data collection. Participants were assured of their anonymity, and all responses were kept confidential and used solely for research purposes.

Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

Data Availability Statement

All data is published in this research article.

Conflicts of Interest

The authors declare no conflict of interest.

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