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Demographic Insights into the Adoption of Digital Innovations in Agriculture: Segmenting Adopters and Non-Adopters among Vietnamese Farmers

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KEYWORDS

Agriculture 4.0,
Digital innovation,
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ABSTRACT

As digital technology adoption expands, it offers significant potential to advance sustainable agricultural practices. This study investigates the segmentation between adopters and non-adopters of digital agricultural technology in Vietnam, drawing on data from 568 farmers. Chi-square tests reveal potential significant associations between adoption status and demographic factors, including age, farm size, revenue, and education levels. These findings outline the key demographic characteristics influencing adoption behavior. To further explore adoption intention, one-way ANOVA and Welch's tests compare intent across different age, experience, and regional groups. While age shows no significant effect, prior experience with agricultural technology is strongly associated with adoption intent, indicating the importance of familiarity with technology. Regional analysis highlights notable variations, with differences observed in adoption intent among farmers in the Central, Northern, and Southern regions. These findings provide valuable insights into the demographic and regional factors influencing digital technology adoption in agriculture. By identifying distinct adoption patterns and understanding potential barriers, the study offers practical guidance for policymakers and stakeholders. Targeted, region-specific strategies can be developed to address unique challenges, encourage broader adoption, and support the transition to high-tech, sustainable farming practices across Vietnam.

1. Introduction

The aggregate change in agricultural labor productivity in Vietnam does not present a favorable picture of an emerging, middle-income nation. Agricultural labor productivty is lower than in many countries with similar income levels, such as the Philippines, Thailand, and Malaysia (World Bank, 2016). Furthermore, the productivity gap between agricultural and non-agricultural labor is certainly growing (Nguyen et al., 2021). Some parts of the country's agricultural work are now primarily part-time or seasonal activities. Many people without formal professions but living in rural areas may only work in agriculture for up to 120 days per year, while joining other labor activities in industrial zones and construction sites for much of the remainder of the year. This helps explain why agricultural productivity is low. Additionally, the dominance of rice in the use the best land and irrigation capacity is yet another factor that affects agricultural aggregate productivity (World Bank, 2016): the value-addition to rice is low,

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which leads to low productivity of labor for rice where production occurs on multiple small parcels under household management.

Considering the over-intensive input use in Vietnam's agricultural sector as another failure of the country's farming practice, OECD (2020) suggests further efforts to be made to control the level of input in agricultural production to improve the sector's competitiveness and sustainability. Vietnam is now facing the issue of increasing negative environmental impact through the process of crop growth intensification. Its agriculture has featured both heavy and inefficient use of fertilizer and pesticides. Every year, more than 10 million tons of fertilizer are used, and about two-thirds of that is used for rice (World Bank, 2016). Fertilizer has acted as the largest single-cost item for each of the crops grown in Vietnam (Liu & Wu, 2021). Around 30-40% of the applied fertilizer is wasted and washed away by water. This challenges the economy and efficiency of agrochemical input used in Vietnam. Moreover, excess fertilizer, together with poor water management practice, leads to a considerable proportion of fertilizer run-off into streams or groundwater, causing serious water pollution (Schreinemachers et al., 2020).

The problem does not stop there. Vietnam is also a heavy user of pesticides, despite the government's effort to encourage integrated pest management solutions (OECD, 2020). The pressure from intensification of crop growth has pushed pesticide use, increasing sharply since the 2000s (World Bank, 2016). The use of pesticides varies from traditional to advanced fewer toxic generics, some of which are no longer permitted in most of Vietnam's agricultural export markets. This has made various products subject to more frequent sampling and testing in strict markets. Together with excessive use of fertilizer, pesticide waste not only negatively affects the environment, but also brings serious health-related risks to Vietnamese farmers (OECD, 2020). Hence there is a need for better practices and technology application to resolve this problem.

This study contributes to the growing body of literature on advanced agricultural technology adoption by providing a detailed analysis of demographic and regional factors associated with farmers' decisions in Vietnam. Unlike many studies that focus on broader technological frameworks, this research delves into the segmentation between adopters and non-adopters, offering a granular perspective on how characteristics such as education, farm size, and prior experience shape adoption behavior. In general, this study aims to answer two research questions:

- RQ1: Is there a significant association between demographic factors (e.g., age, farm size, revenue, education) and the adoption status of digital agricultural technologies among Vietnamese farmers?
- RQ2: Are there significant differences in the mean behavioral intention to adopt digital agricultural technologies across groups based on prior experience with digital tools and regional location?

The regional analysis further enriches the understanding of how geographical contexts influence farmers' openness to digital agricultural innovations. By identifying specific areas where adoption intent is strongest and highlighting gaps in less active regions, this study provides actionable insights for targeted interventions. Moreover, the focus on Vietnam, a country facing unique challenges in agriculture due to land fragmentation and resource constraints, offers a valuable case study for other emerging economies grappling with similar issues. These findings not only inform local policy and stakeholder strategies but also contribute to global discussions on promoting sustainable and inclusive technological advancements in agriculture.

2. Material and methods

2.1. Vietnam's agriculture innovation

Technology is considered the most effective approach to the sustainability of the agricultural sector due to its potential to deal with the national concerns of improving productivity while maintaining the ability to preserve the environment (Luong et al., 2019). However, the current status of technology application in agriculture does not paint a favorable picture. About 66% of farms still rely on manual harvesting; only 10.8% use mechanized processes (Cirera et al., 2021). Findings from the World Bank in 2021 reveal that in Vietnam advanced irrigation systems are mostly used by agricultural firms of larger size and are not popular amongst the majority of farming households (Cirera et al., 2021). In general, Vietnam's high-tech agriculture lags behind other countries, despite a long history of being an agricultural country. With a large number of traditional smallholder farmers, high-tech agriculture remains a vague or relatively unknown concept in Vietnam's rural areas. In 2017, the Prime Minister approved a credit package of USD4.4 billion for high-tech agriculture application loans (BritCham Vietnam, 2021). Nevertheless, it is still challenging for small farming households to apply for that credit package due to their micro-scale nature and lack of collateral. Being aware of the situation, from 2018 to 2020 the government encouraged the development of nearly 500 high-tech agricultural cooperatives (BritCham Vietnam, 2021), which are expected to help individual farmers grow strong together via cooperation in the form of a professional and supportive association.

2.2. Theoretical background

While this study does not delve into causal relationships, it is important to acknowledge the

Theory of Planned Behavior (TPB) as a foundational framework in understanding behavioral intentions. TPB posits that an individual's intention to perform a behavior is influenced by their attitude toward the behavior, subjective norms, and perceived behavioral control (Ajzen, 1991). In the context of agricultural technology adoption, numerous studies have applied TPB to analyze factors influencing farmers' intentions to adopt new practices (Naskar & Lindahl, 2025). For instance, research has shown that behavioral attitude, subjective norms, and perceived behavioral control significantly impact farmers' intentions to adopt ecological agricultural technologies. By considering these components, TPB provides a valuable theoretical background for examining the determinants of technology adoption among farmers.

This research focuses on a descriptive analysis of demographic factors influencing the adoption of digital agricultural technologies, utilizing theories such as Human Capital Theory, Regional Development Theory, Socioeconomic Status, and Technology Adoption Theory.

2.2.1. Human Capital Theory

Human capital theory posits that education, skills, and experience enhance individuals' capacity to adopt and use new technologies (Becker, 1964). Farmers with higher education levels or prior exposure to agricultural innovations are more likely to perceive and leverage the benefits of digital tools. This aligns with the study's findings, which highlight the significant role of education and experience in influencing adoption behavior.

2.2.2. Regional Development Theory

Regional development theory suggests that differences in infrastructure, institutional support, and market access shape regional adoption patterns (Stöhr & Taylor, 1981). The study's findings of varying adoption intent across regions emphasize the importance of geographic and contextual factors. For example, farmers in the Central region exhibiting higher adoption intent may reflect better access to infrastructure or targeted support programs.

2.2.3. Socioeconomic Status and Technology Adoption

Socioeconomic factors, including income and farm size, are critical in determining access to and adoption of new technologies (Jensen, 2007). Larger farm sizes and higher revenues typically provide farmers with the financial means and perceived necessity to invest in advanced tools. Conversely, smallholder farmers may face financial constraints or perceive lower immediate benefits, reducing their likelihood of adoption. These dynamics are reflected in the study's results, which show significant associations between farm size, revenue, and adoption status.

2.3. Methods

Data collection for this study involved surveying rice farmers across various regions of Vietnam to gather comprehensive insights into their adoption behavior and intentions regarding advanced digital agricultural technologies. The study collected 602 responses between August 2022 to April 2023. However, during the data screening process, 34 responses were removed from the dataset due to incompleteness and the presence of outliers. The removal of these cases ensured the quality and reliability of the dataset, preventing potential distortions in the statistical analysis. A total of 568 responses were validated for analysis, ensuring a robust dataset for meaningful conclusions. The survey captured key demographic information, including age, education, farm size, and income, and location (e.g., North, Central, or South of Vietnam) to identify the differences in adoption intention. Additionally, farmers were asked about their current adoption status, categorizing them as adopters or non-adopters of existing digital agricultural tools. To assess future adoption potential, the survey also measured their behavioral intention to adopt advanced technologies. This approach provided a holistic understanding of the factors shaping both current and prospective technology adoption among rice farmers in Vietnam.

The study employed a combination of systematic and cluster sampling to ensure a balanced and representative sample of farmers across different regions of Vietnam. Survey responses were collected from farmers who attended agricultural conferences organized by supporting companies in various provinces. This approach allowed the researchers to reach a diverse group of farmers while maintaining a structured sampling strategy. To achieve geographical diversity, the sampling process began with the categorization of provinces into three major regions: North, Central, and South Vietnam. Within each region, provinces were ranked based on their agricultural production values to ensure representation from areas with varying levels of agricultural activity. Following this ranking, the researchers systematically selected seven provinces per region, ensuring that a total of 21 provinces were included in the study. This step ensured that provinces with both high and low agricultural output were proportionally represented in the sample.

Once the provinces were selected, the researchers attended agricultural conferences in these locations, where farmers from different districts gathered. To recruit participants, a systematic sampling approach was applied: every 5th farmer passing by the survey booth or research team was invited to complete the survey. This method minimized selection bias while ensuring that a diverse set of farmers participated in the study. By integrating systematic and cluster sampling, the study effectively captured a broad representation of farmers across different regions and farming conditions in Vietnam. This methodological approach strengthened the validity of the findings, particularly in analyzing technology adoption patterns and behavioral intentions among Vietnamese farmers.

This study divided the sample into two groups: farmers who had not applied any kind of digital agricultural technology (non-adopters) and farmers who had applied some kinds (adopters). For this research, those who selected "I have utilized agricultural technologies in my farming practices" are considered adopters, and those who chose "I am aware of agricultural technologies but have not attempted to use them" are considered non-adopters. Agricultural technology here means the use of general tools, such as tractors, irrigation systems, seed drills, planters, fertilizer spreaders, harvesting equipment, pest control tools (e.g., insecticides or traps), and so on. It does not include the entire gamut of precision agriculture techniques. The purpose of this analysis was to examine whether there were any significant differences between these groups based on demographic characteristics (e.g., age, farm size, revenue, and educational level).

Chi-square tests were utilized to investigate how these demographic variables are associated with the decision of the two groups of adopters and non-adopters. The Chi-square test for independence is a non-parametric statistical method used to determine if there is a potential relationship between two categorical variables from the same sample (Pallant, 2020). The test begins with the null hypothesis that there is no association between them. The alternate hypothesis suggests that the two are associated. The decision to accept or reject the null hypothesis depends on the p-value derived from the Chi-square statistic: if the p-value is lower than the predetermined significance level, the null hypothesis is rejected, i.e., the two variables are not independent, and the alternate hypothesis of a potential association between the two is accepted (Pallant, 2020). In this research, a significance level of 0.05 ($p < 0.05$) was used as the threshold for determining statistical significance. This ensures that the research can identify potential associations without being overly restrictive, which is particularly important given the exploratory nature of this research.

Like any statistical technique, the Chi-square test has specific assumptions about the data, including that the sampling method is random and that the sample size is large enough. Both variables must be categorical, and the expected frequency of any sub-category of the two variables should be at least 5. To ensure that none of these assumptions was violated, a preliminary data check was carried out, which found that all assumptions were satisfied for all variables involved (Table 5).

The one-way ANOVA test here encompasses several components to provide a comprehensive analysis of farmers' BI items related to the adoption of PA technology. Initially, the Levene's test is employed to assess the homogeneity of variance among the groups. If the Levene's test significance value is greater than 0.05, the F-test significance value from the ANOVA table should be used for further interpretation and analysis (Pallant 2020). In cases where there are significant differences in variances, the Welch or Brown-Forsythe tests should used to examine mean differences between groups (Pallant 2020). While both tests serve a similar purpose, their approaches differ, which may lead to inconsistent results. However, researchers tend to favor the Welch test due to its robustness and wider applicability (Tabachnick et al. 2013). Similar to the Chi-square test, statistical significance is determined using $p < 0.05$, ensuring consistency in hypothesis testing across different statistical methods.

The one-way analysis of variance (ANOVA) test is a statistical method used to compare the means of three or more independent groups and determine if there are any significant differences among them (Pallant, 2020). In this paper, one-way ANOVA tests are presented to examine the differences in responses to the behavioral intention (BI) items of farmers across distinct groups age and experience groups. Additionally, this study aims to account for the differences between regions where farmers operate, with the goal of generating targeted recommendations to facilitate the adoption of PA technology.

3. Results and Discussion

3.1. Respondent segmentation - Adopters vs. Non-adopters of agricultural technology

3.1.1. Age observation

Table 1 presents the age distribution of respondents in terms of adopters and non-adopters of agricultural technologies. Among the adopters, 36 (17.6% of total adopters) were in the 20-29 age group, 45 (22.0%) in the 30-39 age group, 45 (22.0%) in the 40-49 age group, 49 (23.9%) in the 50-59 age group, and 30 (14.6%) were above 60. Among non-adopters, 21 (5.8% of total non-adopters) were in the 20-29 age group, 85 (23.4%) in the 30-39 age group, 120 (33.1%) in the 40-49 age group, 90 (24.8%) in the 50-59 age group, and 47 (12.9%) were above 60. Hence the distribution of respondents within each age group shows different proportions of adopters and non-adopters. The Chi-square in Table 5 also indicates a significant ($p < 0.05$) association between adopting agricultural technology and the respondent's age group, with $\chi^2(4) = 24.107$ and $p = 0.000$. This significance can be observed by the gaps between the percentages of adopters and non-adopters.

3.1.2. Farm size observation

For the observation of farm size, Table 2 presents the distribution across the adopters and non-adopters. Among adopters, three (1.5%) had farms no larger than 500m², 47 (22.9%) possessed farms from 500m² to 1ha, 76 (37.1%) owned farms between 1ha and 1.5ha, 54 (26.3%) from 1.5ha to 2ha, and 25 (12.2%) owned farms larger than 2ha. Among non-adopters, 26 (7.2% of total non-adopters) had farms no larger than 500m², 249 (68.6%) owned farms ranging from 500m² to 1ha, 45 (12.4%) farms between 1ha and 1.5ha, 23 (6.3%) managed farms from 1.5ha to 2ha, and 20 (5.5%) had farms larger than 2ha.

The Chi-square test result (Table 5: $\chi^2 = 144.285$; df=4) reveals a highly significant association between farm size and adoption of agricultural technologies (with p-value = 0.000). This can be further observed by examining the proportions of adopters and non-adopters within each farm size category (Table 3). The comparison highlights the varying proportions of

Table 1. Age observations for adopters and non-adopters of agricultural technologies

	Adopters			Non-adopters			Total	
	Frequency	% within adopters	% within age groups	Frequency	% within non-adopters	% within age groups	Age freq.	% within sample
20-29	36	17.6%	63.2%	21	5.8%	36.8%	57	10.0%
30-39	45	22.0%	34.6%	85	23.4%	65.4%	130	22.9%
40-49	45	22.0%	27.3%	120	33.1%	72.7%	165	29.0%
50-59	49	23.9%	35.3%	90	24.8%	64.7%	139	24.5%
Above 60	30	14.6%	39.0%	47	12.9%	61.0%	77	13.6%
Total	205	100%	-	363	100%	-	568	100%

Table 2. Farm size observations for adopters and non-adopters of agricultural technologies

	Adopters			Non-adopters			Total	
	Frequency	% within adopters	% within size groups	Frequency	% within non-adopters	% within size groups	Size freq.	% within sample
≤ 500m²	3	17.6%	10.3%	26	7.2%	89.7%	29	5.1%
500m² to 1 ha	47	22.0%	15.9%	249	68.6%	84.1%	296	52.1%
1 ha to 1.5 ha	76	22.0%	62.8%	45	12.4%	37.2%	121	21.3%
1.5 ha to 2 ha	54	23.9%	70.1%	23	6.3%	29.9%	77	13.6%
Bigger than 2 ha	25	14.6%	55.6%	20	5.5%	44.4%	45	7.9%
Total	205	100%	-	363	100%	-	568	100%

Table 3. Revenue observations for adopters and non-adopters of agricultural technologies

	Adopters			Non-adopters			Total	
	Frequency	% within adopters	% within rev. groups	Frequency	% within non-adopters	% within rev. groups	Rev. freq.	% within sample
<VND200 mil	48	23.4%	16.0%	252	69.4%	84.0%	300	52.8%
VND 200 mil to VND 399 mil	74	36.1%	51.7%	69	19.0%	48.3%	143	25.2%
VND 400 mil to VND 599 mil	59	28.8%	66.3%	30	8.3%	33.7%	89	15.7%
VND 600 mil to VND 999 mil	24	11.7%	66.7%	12	3.3%	33.3%	36	6.3%
Total	205	100%	-	363	100%	-	568	100%

adopters and non-adopters within each size category, offering valuable insights into the association between potential factors associated with farm size (e.g., resource availability and economies of scale) and the adoption of agricultural technologies.

3.1.3. Revenue observation

Among the 205 adopters, 48 (23.4%) had revenues below VND 200 million (USD8,500), 74 (36.1%) between VND 200 million and 399 million (USD17,000), 59 (28.8%) from VND 400 million to 599 million (USD25,500), and 24 (11.7%) reported revenues ranging from VND 600 million to VND 999 million (USD42,600). Of the 363 non-adopters, 252 (69.4%) had revenues below VND 200 million, 69 (19.0%) between VND 200 million and 399 million, 30 (8.3%) from VND 400 million to 599 million, and 12 (3.3%) within the VND 600 million to 999 million range (Table 3). Thus, it can be inferred that a potential relationship exists between revenue levels and the adoption of agricultural technologies. The Chi-square results in Table 5 (χ^2 (3) = 117.448, $p < 0.05$) validate a significant link between revenue levels and that adoption. The patterns observed suggest variations in adoption behavior across different revenue categories, highlighting differences in financial capacity or access to resources among participant groups, including those who have adopted and those who have not adopted technology. This distribution may reflect varying levels of investment capability, availability of funding opportunities, or economic considerations influencing decision-making.

3.1.4. Education observation

In regard to education, Table 4 shows that the majority of adopters were secondary school (63, 30.7% of total adopters) and high school (42, 20.5%) graduates; 35 (17.1%) had completed primary school, 33 (16.1%) had vocational school education, and 32 (15.6%) held college or university degrees. For non-adopters, 88 (24.2%) had completed primary school, 133 (36.6%) were secondary school graduates, 102 (28.1%) had high school education, 39 (10.7%) had attended vocational schools, and only one (0.3%) had a college or university degree. The Chi-square results in Table 5 indicate a significant association between education level and technology adoption (χ^2 (4) = 63.415, $p < 0.05$ The distribution reflects different educational backgrounds among participant groups, including those who have adopted and those who have not adopted technology, suggesting variations in exposure to new information, familiarity with technology, or accessibility to training opportunities.

Recent studies have demonstrated that demographic factors significantly influence the adoption of digital agricultural technologies among farmers. For instance, a study by Ben Hassen et al. (2024) found that in low and middle-income countries, higher education levels and larger farm sizes are positively associated with technology adoption. Similarly, research by Lei and Yang (2024) in China's Guangdong Province indicated that the adoption of digital technologies leads to increased income among farmers, with those managing larger cultivation areas showing higher adoption intensity. These findings align with the current study's Chi-square test results, which reveal significant associations between demographic factors—such as age, education, farm size, and income—and the adoption of digital agricultural technologies among Vietnamese rice farmers.

3.2. *Comparison of intention to adopt across Age, Experience, and Region groups*

For the comparison of age groups (see Table 6), the Levene's Test significance value (sig.) is 0.834, which is greater than 0.05. This indicates that the assumption of homogeneity of variance is met, meaning the variance in behavioral intention (BI) scores is similar across age groups. Therefore, the F-test significance value from the ANOVA table is used for further interpretation and analysis. The F-test significance value (sig.) is 0.058 (Table 7), which is greater than 0.05. This result suggests that there is no statistically

Table 4. Educational level observations for adopters and non-adopters of agricultural technologies

	Adopters			Non-adopters			Total	
	Frequency	% within adopters	% within ed. groups	Frequency	% within non-adopters	% within ed. groups	Ed. freq.	% within sample
Primary school	35	17.1%	28.5%	88	24.2%	71.5%	123	21.7%
Secondary school	63	30.7%	32.1%	133	36.6%	67.9%	196	34.5%
High school	42	20.5%	29.2%	102	28.1%	70.8%	144	25.4%
Vocational school	33	16.1%	45.8%	39	10.7%	54.2%	72	12.7%
College and university	32	15.6%	97.0%	1	0.3%	3.0%	33	5.8%
Total	205	100%	-	363	100%	-	568	100%

Table 5. Expected frequencies for adopters and non-adopters and results of Chi-square tests

Demographic variables		Adopter expected freq.	Non-adopter expected freq.	Chi-squared	df	Significance
Age	20-29	21	36	24.107	4	.000
	30-39	47	83			
	40-49	60	105			
	50-59	50	89			
	Above 60	28	49			
Farm size	≤ $500m^2$	11	19	144.285	4	.000
	$500m^2$ to 1ha	107	189			
	1ha to 1.5ha	44	77			
	1.5ha to 2ha	28	49			
	Bigger than 2ha	16	29			
Revenue	<VND 200 mil	108	192	117.448	3	.000
	VND 200 mil to VND 399 mil	52	91			
	VND 400 mil to VND 599 mil	32	57			
	VND 600 mil to VND 999 mil	13	23			
Educational level	Primary school	44	79	63.415	4	.000
	Secondary school	71	125			
	High school	52	92			
	Vocational school	26	46			
	College and university	12	21			

Table 6. Test of Homogeneity of Variances for Age groups

Test of Homogeneity of Variances					
		Levene Statistic	df1	df2	Sig.
BI_Average	Based on Mean	.364	4	563	.834
	Based on Median	.158	4	563	.960
	Based on Median and with adjusted df	.158	4	541.998	.960
	Based on trimmed mean	.307	4	563	.873

Table 7. ANOVA for Age groups

ANOVA – F test					
BI_Average					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2.894	4	.724	2.292	.058
Within Groups	177.751	563	.316		
Total	180.646	567			

significant difference in BI among respondents of different age groups. In other words, BI scores do not vary systematically by age group, and any observed differences in means are likely due to random variation rather than a meaningful distinction between groups. This finding indicates that age, as categorized in this study, does not differentiate respondents in terms of their BI toward adopting PA technology.

In the case of experience groups, the Levene's Test significance value (sig.) is 0.021, which is less than 0.05 (Table 8). This indicates that the assumption of homogeneity of variance is violated, meaning the variance in BI scores differs across experience groups. As a result, the Welch test, which is more robust in handling unequal variances, is used for further examination and interpretation. The Welch test significance value (sig.) is 0.001 (Table 9), which is less than 0.05. This result suggests a statistically significant difference in BI scores among respondents with varying levels of experience with agricultural technology. In other words, behavioral intention to adopt PA technology is not uniform across experience groups, indicating that respondents' prior engagement with agricultural technology is associated with differences in their BI scores. To provide explanation for the difference, this research investigated the discussion from global academia. Experience with technology equips farmers with better risk assessment skills, enabling them to evaluate the potential benefits and challenges of new agricultural technologies more effectively. This informed perspective fosters a greater openness to adoption. Furthermore, prior technology use enhances farmers' understanding and familiarity with modern agricultural practices, reducing the learning curve associated with new innovations and increasing the likelihood of adoption.

For the regional comparison, the Levene's Test significance value (sig.) is 0.508, which is greater than 0.05 (Table 10). This indicates that the assumption of homogeneity of variance is satisfied, meaning that the variance in BI scores is consistent across different regions. As a result, the F-test significance value from the ANOVA table is used for further analysis and interpretation. The F-test significance value (sig.) is less than 0.0001 (Table 11), indicating a statistically significant difference in BI among respondents from

Table 8. Test of Homogeneity of Variance for groups of Experience in using technology

Test of Homogeneity of Variances					
		Levene Statistic	df1	df2	Sig.
BI_Average	Based on Mean	5.386	1	566	.021
	Based on Median	3.537	1	566	.061
	Based on Median and with adjusted df	3.537	1	544.164	.061
	Based on trimmed mean	3.816	1	566	.051

Table 9. Welch's test for Experience groups

Robust Tests of Equality of Means				
BI_Average				
	Statistic[a]	df1	df2	Sig.
Welch	10.506	1	492.634	.001

a. Asymptotically F distributed.

Table 10. **Test of Homogeneity of Variances for Region groups**

Test of Homogeneity of Variances					
		Levene Statistic	df1	df2	Sig.
BI_Average	Based on Mean	.678	2	565	.508
	Based on Median	.390	2	565	.677
	Based on Median and with adjusted df	.390	2	543.990	.677
	Based on trimmed mean	.751	2	565	.472

Table 11. ANOVA test for Region groups

ANOVA					
BI_Average					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	8.854	2	4.427	14.589	.000
Within Groups	171.450	565	.303		
Total	180.304	567			

different regions. This result suggests that behavioral intention to adopt PA technology varies across geographic areas, meaning that location is associated with differences in BI scores. To offer an elaboration on the differences in terms of regions, this research synthesized the literature. Generally, the disparity in technology adoption across Vietnam's regions could stem from factors such as production scale, climate conditions, and corporate involvement (Nguyen et al., 2024). In the Central Highlands, extensive agricultural land and favorable climate have promoted concentrated farming areas that employ advanced technologies for key crops like coffee, rubber, and pepper. The presence of major agricultural enterprises further facilitates investment and technology transfer in this region. Conversely, the Northern region, particularly the midland and mountainous areas, faces challenges in adopting high-tech agriculture due to complex terrain and fragmented, small-scale production (Nguyen et al., 2023). Although the number of cooperatives collaborating with farmers to implement high-tech solutions increased from 198 in 2019 to 693 in 2023, technology access remains limited because of insufficient investment and underdeveloped infrastructure (Nguyen et al., 2024). To enhance high-tech agricultural practices in the North, appropriate support policies, infrastructure development, and encouragement of corporate participation are essential. The Southern region of Vietnam, particularly the Mekong Delta, exhibits a higher potential for agricultural production compared to the Northern region (Kaila, 2015). This is attributed to its extensive, fertile lands and favorable climate, which support large-scale cultivation of crops like rice and fruit. In contrast, the Northern region faces challenges such as complex terrain and fragmented, small-scale farming, limiting its agricultural expansion (Ferrer et al., 2023). These geographical and environmental disparities contribute to the differences in agricultural productivity and technology adoption between the two regions.

In summary, the mean comparison test results showed that age did not have a substantial impact on the behavioral intention of respondents to adopt PA technology. In contrast, experience with agricultural technologies played a role in shaping BI. Additionally, regional differences were found to be notably associated with BI.

The mean comparison analysis in this study indicates that prior experience with agricultural technologies is significantly associated with a higher intention to adopt advanced digital tools among Vietnamese rice farmers. This finding aligns with recent research emphasizing the importance of technological familiarity in adoption decisions. For instance, it is found that factors related to the technological familiarity of farmerssignificantly impact perceived usefulness and ease of use, which in turn affect the intention to adopt Agriculture 5.0 technologies among farmers in Nepal. Similarly, a study on Bavarian farmers reported that established use of entry technologies increased the probability of adopting additional digital technologies, highlighting the role of prior experience in technology adoption. These studies suggest that enhancing farmers' exposure to and familiarity with existing technologies can positively influence their willingness to adopt more advanced digital agricultural innovations.

4. Conclusion

This study highlights key differences between adopters and non-adopters of digital agricultural technologies in Vietnam, focusing on demographic and regional characteristics that shape adoption behavior and intent. The Chi-square test results indicate potential associations between educational level, age group, farm size, and revenue with the adoption of digital agricultural technologies, highlighting the need for targeted strategies to enhance adoption. Farmers with lower education levels may require structured training programs and hands-on demonstrations to familiarize themselves with digital tools, while extension services and cooperatives can serve as key facilitators in bridging knowledge gaps. Differences in age groups suggest that younger farmers may benefit from online learning platforms and mobile-based training, whereas older farmers may require in-person guidance and peer-to-peer learning opportunities. Regarding farm size, larger farms may be more capable of adopting advanced technology, while smallholder farmers could benefit from subsidies, leasing programs, and cooperative-based technology sharing to reduce financial barriers. Additionally, farmers with lower revenue levels may face constraints in investing in technology, necessitating financial support mechanisms such as microfinance, digital technology grants, and government-backed credit programs to facilitate access. By implementing targeted educational support, scalable financial assistance, and accessible digital solutions, policymakers and agricultural stakeholders can foster a more inclusive and sustainable digital transformation in Vietnam's agricultural sector.

The results from mean comparisons of behavioral intention to adopt between different groups of farmers (e.g., regions and experience) also suggest some initiatives that could be taken. The importance of prior experience with agricultural technologies suggests that fostering familiarity with basic digital tools through pilot projects or demonstrations can build farmers' confidence and readiness for more advanced technologies. Extension services and local cooperatives can play a crucial role in facilitating these initiatives. Regional differences in adoption intent highlight the need for localized strategies. For instance, farmers in the Central region may benefit from enhanced infrastructure and access to advanced technology offerings, while those in the North could require targeted awareness campaigns and incentives to support adoption efforts. Meanwhile, in the South, particularly in the Mekong Delta, where agriculture is highly commercialized and export-oriented, farmers may be more inclined to adopt new technologies that enhance efficiency and sustainability. However, challenges such as climate change impacts, including salinity intrusion and rising sea levels, necessitate targeted interventions that emphasize climate-smart technologies and precision farming solutions tailored to the region's unique agricultural conditions.

These results call for collaboration among government agencies, private sectors, and local stakeholders to design inclusive, region-specific policies that address the unique challenges faced by different farmer groups. By doing so, Vietnam can accelerate the adoption of digital innovations, improving agricultural productivity, sustainability, and economic resilience across its farming communities. Accelerating digital transformation in agriculture requires expanding rural connectivity and infrastructure. Many advanced technologies, such as precision farming, remote sensing, and automated irrigation systems, rely on stable internet access and digital literacy. Policymakers should focus on improving broadband coverage in agricultural regions and fostering public-private partnerships to invest in digital infrastructure that supports smart farming solutions.

While this study provides valuable insights into the segmentation of adopters and non-adopters of digital agricultural technology in Vietnam, a few limitations should be noted. First, although the sampling strategy combined systematic and cluster sampling to ensure coverage across different regions, the data were collected from farmers attending agricultural conferences. While these events bring together a diverse range of farmers, the sample may not fully represent those who do not participate in such gatherings. However, including farmers from 21 provinces across North, Central, and South Vietnam helps provide a broad perspective on adoption patterns. Second, while the statistical analyses identify significant differences between groups based on demographic and regional factors, the study does not establish causal relationships. The results indicate associations rather than direct effects, and other unobserved factors, such as policy interventions or farm-specific characteristics, may also contribute to adoption behavior.

Building on the findings and limitations of this study, future research could explore several areas to enhance the understanding of digital agricultural technology adoption among farmers in Vietnam. Expanding the sampling approach could help improve the generalizability of findings. While this study relied on farmers attending agricultural conferences, future research could incorporate randomized field surveys or longitudinal studies to capture a broader spectrum of farmers, including those in more remote or less commercially integrated areas. Additionally, future studies could investigate differences between smallholder farmers and large-scale producers to understand how farm size and market integration influence adoption behavior. Furthermore, future research could apply causal modeling approaches, such as structural equation modeling (SEM) or experimental interventions, to better understand the mechanisms driving adoption. For example, studies could examine how financial incentives, extension services, or training programs influence behavioral intention and actual technology uptake over time. Also, qualitative research could provide deeper insights into farmers' perceptions, motivations, and barriers to adopting digital agricultural technology. In-depth interviews and focus group discussions could help uncover social, cultural, and economic factors that shape decision-making, particularly in regions where adoption rates differ.

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