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Factors Influencing Farmers' Decision to Apply Internet of Things Technology in Vegetable Production in Lam Dong Province

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KEYWORDS

IoT adoption,
Lam Dong province,
smart agriculture,
technology adoption,
vegetable farming.

ABSTRACT

This study investigates the factors influencing the adoption of Internet of Things (IoT) technologies among vegetable farmers in Lam Dong province, Vietnam. Using binary logistic regression analysis, the study identifies key determinants driving IoT adoption, including education level, farming experience, share of vegetable income, interest in IoT, and access to IoT technology. Results show that farmers with higher education and more farming experience are more likely to adopt IoT solutions, while strong interest and easier access significantly increase adoption probabilities. Conversely, variables such as age, land size, investment capital, and overall household income did not exhibit significant impacts on IoT adoption. The findings highlight the importance of education, technical training, infrastructure development, and financial support in promoting IoT adoption. The study recommends targeted policies, including subsidies, training programs, and awareness campaigns, to enhance IoT adoption and ensure sustainable agricultural development. These insights can guide policymakers, agricultural extension services, and technology providers in promoting smart farming practices, ultimately boosting productivity and resilience among vegetable farmers in Lam Dong province.

1. Introduction

In the context of the Fourth Industrial Revolution, the application of scientific and technological advancements, particularly the Internet of Things (IoT), has become an inevitable trend in agricultural production to enhance productivity, quality, and economic efficiency (De Clercq et al., 2018). IoT in agriculture enables the monitoring and automation of processes such as irrigation, fertilization, and crop health tracking through sensors, allowing farmers to manage cultivation more precisely and optimize resources (Wolfert et al., 2017). IoT contributes to reducing production costs, minimizing chemical usage, and enhancing product traceability, meeting modern market standards (Nikkilä et al., 2010). In Vietnam, the application of IoT technology in agriculture has been implemented in many key production regions such as the Mekong Delta, Central Highlands, and Southeastern areas. According to the Ministry of Agriculture and Rural Development (MARD, 2022), the application of high technology, including IoT, has increased crop yields by 20-30% and reduced input costs by 25% compared to traditional farming. However, the adoption of IoT still faces several challenges, including high initial investment costs, lack of technical knowledge,

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and limited access to support services, especially for smallholder farmers (Nguyễn Thị Lan, 2017).

Lam Dong, with its favorable soil and climate conditions, is the largest vegetable-producing province in Vietnam, supplying approximately 40% of the country's total clean vegetable output for both domestic consumption and export. However, agricultural production in Lam Dong still primarily relies on traditional farming practices, characterized by the extensive use of chemical fertilizers and pesticides, which negatively affect the environment and product quality. In this context, the application of IoT emerges as an effective solution for promoting sustainable, eco-friendly smart agriculture. Besides farmers' decisions to adopt IoT depend not only on economic benefits but also on other factors such as educational background, farming experience, interest in technology, and access to support services (Nguyễn Tuấn Kiệt & Nguyễn Tấn Phát, 2019; Nam et al., 2021). Zhang et al. (2002) also emphasized the role of agricultural extension policies and financial support in encouraging farmers to adopt new technologies. Given this context, this study aims to analyze the factors influencing the decision to adopt IoT technology in vegetable production among farmers in Lam Dong province. The findings not only identify the barriers and drivers of IoT adoption but also provide a scientific basis for developing appropriate support policies, contributing to enhancing productivity, product quality, and sustainable income for farmers.

2. Literature review

2.1. Internet of Things (IoT) in agriculture

The adoption of the IoT in agriculture offers significant economic and social benefits, transforming traditional farming practices into more efficient, sustainable, and profitable operations. IoT technologies enable real-time data collection and analysis, which supports precision agriculture, resource optimization, and improved decision-making. These advancements not only enhance productivity and profitability but also contribute to environmental sustainability and social well-being.

IoT technologies facilitate precision agriculture, which optimizes planting, watering, and fertilization processes. This can lead to a 10-20% increase in crop yields and a 20-30% improvement in water usage efficiency, ultimately boosting profitability for farmers (Anand Kumar, 2024; Bhor et al., 2025). By enabling precise administration of resources such as water, fertilizers, and pesticides, IoT reduces wastage and operational costs. This efficient resource management contributes to cost savings and increased profitability (Balakrishnan et al., 2024). IoT integration allows farmers to produce higher quality crops, which can command better prices in the market. This competitive edge is crucial for farmers in regions facing economic challenges (Manjula & Godihal, 2024).

Moreover, there are numerous social benefits arose from the adoption of IoT in agriculture. By increasing agricultural productivity and efficiency, IoT technologies contribute to enhanced food security, addressing the rising global food demand (Duguma & Bai, 2024). IoT enables environmentally friendly farming by reducing the need for excessive chemical treatments and minimizing soil and water pollution. This promotes biodiversity and eco-conscious agricultural practices (Abi et al., 2024). IoT provides farmers with actionable insights and data-driven decision-making capabilities, empowering them to optimize their operations and improve their livelihoods. This empowerment is particularly significant in regions with limited access to modern farming techniques (Al-Tulaibawi et al., 2024).

While the benefits of IoT in agriculture are substantial, several challenges must be addressed to ensure widespread adoption. High initial costs, connectivity issues, and data security concerns are significant barriers that need to be overcome. Additionally, there is a need for adequate infrastructure and training for farmers to fully leverage IoT technologies (Nofriyanti & Hipma, 2024). Collaborative efforts among stakeholders, including researchers, policymakers, and technology providers, are essential to developing sustainable solutions and facilitating broader IoT adoption in agriculture (Abi et al., 2024; Balakrishnan et al., 2024).

While existing literature highlights the benefits and challenges of IoT adoption in agriculture, few studies have explored the specific context of vegetable farming in Lam Dong province, where IoT adoption is still in its early stages. Moreover, there is limited empirical evidence on how socio-economic factors, technological awareness, and institutional support influence farmers' adoption decisions. Therefore, this study seeks to fill this gap by analyzing the determinants of IoT adoption among vegetable farmers in Lam Dong, providing insights for policymakers, agricultural extension services, and technology providers.

2.2. Study area

Lam Dong, located in the South-Central Highlands of Vietnam, spans an area of over 9,773 km² with an elevation ranging from 300 to 1,500 meters above sea level. This altitude provides the province with an ideal temperate climate, maintaining temperatures between 18 and 25°C, making it particularly favorable for vegetable and flower cultivation. The province has a population of over 1.3 million people. Geographically, Lam Dong is bordered by Binh Thuan province to the south and southeast, Khanh Hoa and Ninh Thuan provinces to the east, Dak Lak and Dak Nong provinces to the north, and Dong Nai and Binh Phuoc provinces to the southwest. Administratively, Lam Dong comprises 12 units, including two cities and ten districts.

3. Methodology

3.1. Data collection

The minimum sample size for the multivariable regression model is calculated using the formula: N = 8*var + 50 (Tabachnick et al., 2013), where N represents the sample size and var refers to the number of independent variables included in the regression model. In this study, the regression model includes nine independent variables, resulting in a minimum sample size of 50 + 8*9 = 122.

For this research, the author will conduct surveys and interviews with 65 households cultivating vegetables using IoT technology and 65 households practicing traditional vegetable farming without IoT application. These households will be selected from one city and four districts: Da Lat, Duc Trong, Don Duong, Lam Ha, and Lac Duong. Thus, the total sample size for this study will be 130 farming households, with the focus on two specific vegetable crops—tomatoes and bell peppers. The sample size is evenly distributed between the IoT and traditional farming models.

According to Lam Dong Statistical Office (2023), these five selected areas accounted for nearly 64% of the total vegetable-growing area in the province in 2022. Specifically, Don Duong and Duc Trong districts alone contributed over 50,000 hectares, while Da Lat, Lac Duong, and Lam Ha also maintained stable and expanding vegetable production areas from 2018 to 2022. These districts are also home to high-tech and smart agriculture zones promoted by provincial authorities. Lam Dong province has recognized and developed 10 specialized zones for high-tech vegetable production with a total area of approximately 10,000 hectares, mainly concentrated in the selected districts (Da Lat, Duc Trong, Don Duong, Lam Ha, and Lac Duong). Furthermore, these areas are projected to play a critical role in reaching the province's target of 95,500 hectares of safe vegetable cultivation by 2030.

3.2. Data analysis

Logistic regression is the most suitable method for this study as it analyzes the binary decision of IoT adoption among farming households—whether a household adopts IoT technology (coded as 1) or not (coded as 0). Unlike linear regression, logistic regression applies a logit transformation, ensuring predicted probabilities remain between 0 and 1, making it ideal for modeling decision outcomes (Hosmer Jr et al., 2013)

This method allows for the estimation of how independent variables, such as age, education, land size, and investment capital, influence the likelihood of IoT adoption. The resulting odds ratios provide interpretable insights, indicating how a one-unit change in each factor affects the probability of adoption while holding other variables constant (Menard, 2002).

Logistic regression also accommodates both continuous and categorical predictors and does not require normal distribution, making it robust for real-world agricultural data (Agresti, 2018). Therefore, it ensures reliable analysis of the key factors driving or hindering IoT adoption in vegetable production.

The Binary Logistic Regression model is employed to analyze the factors influencing the decision of farming households in Lâm Đồng province to adopt IoT technology in vegetable production. This method estimates how each independent variable affects the likelihood of IoT adoption. When other factors are held constant, an increase of one unit in an independent variable X_n changes the probability of the dependent variable (IoT adoption) from an initial probability P_0 to a new probability P_1, calculated using the following formula:

$$P_1 = \frac{P_0 \times e^{\beta n}}{1 - P_0 \times (1 - e^{\beta n})} (1) \qquad (1)$$

This formula indicates that, while holding other variables constant, a one-unit increase in X_n results in a shift in the probability of IoT adoption from P_0 to P_1.

In this study, the Binary Logistic Regression model is applied to identify the factors affecting IoT adoption decisions. The regression equation is expressed as:

$$Logit(P) = \ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_n X_2 \quad (2)$$

Where P_i represents the probability of the event occurring (1 if the household adopts IoT; 0 if not). This equation can be rewritten as:

$$P_i = \frac{e^{\beta_0 + \beta_1 X_1 + ... + \beta_{nk} X_k}}{1 + e^{\beta_0 + \beta_1 X_1 + ... + \beta_{nk} X_k}} \qquad (3)$$

The final logistic model is expressed as:

$$\ln\left[\frac{P(Y=1)}{1 - P(Y=1)}\right] = Z_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + ... + \beta_9 X_9 \quad (4)$$

P(Y=1): Probability that the household adopts IoT in vegetable production. P(Y=0): Probability that the household does not adopt IoT. β_0 is the intercept term. $\beta_1, \beta_2, \ldots, \beta_9$ are Regression coefficients corresponding to each independent variable $X_1, X_2, \ldots, X_9$.

The logistic regression model used in this study includes nine independent variables that are hypothesized to influence the decision of farming households in Lâm Đồng province to adopt IoT technology in vegetable production. Each variable reflects a specific socio-economic or technological factor that affects the likelihood of adoption.

Age of Farmer (X_1): Age represents the number of years of the primary decision-maker involved in agricultural production. Older farmers are often expected to have more experience, which may positively influence their decision to adopt advanced technology (Nguyễn Văn Thiệu & Nguyễn Thị Ngọc Dung, 2014).

Education Level (X_2): Education level is measured by the number of years of formal schooling completed by the farmer. Higher education is associated with better comprehension of new technologies, increased awareness of IoT benefits, and greater willingness to adopt innovative farming practices. Farmers with higher education levels are more likely to seek out and apply IoT solutions to enhance productivity and sustainability (Võ Văn Tuấn & Lê Cảnh Dũng, 2015).

Farming Experience (X_3): Farming experience, measured in years, reflects the time farmers have spent cultivating crops. Greater experience usually correlates with better farming management skills and an understanding of the challenges associated with traditional practices. Experienced farmers are more likely to recognize the potential benefits of IoT in overcoming production challenges (Nguyễn Tuấn Kiệt & Nguyễn Tấn Phát, 2019; Nam et al., 2021).

Cultivated Land Area (X_4): This variable represents the total land area used for vegetable production, measured in 1,000 square meters. Larger farm sizes typically provide greater incentives for technology adoption, as IoT systems can optimize resource allocation, improve productivity, and enhance cost-efficiency on larger plots (Thùy et al., 2021).

Investment Capital (X_5): Investment capital refers to the amount of money allocated for vegetable production, measured in million VND. Farmers with higher investment capacity are more likely to afford the initial costs associated with IoT adoption, including equipment, installation, and maintenance (Nguyễn Văn Thiệu & Nguyễn Thị Ngọc Dung, 2014).

Household Income from Vegetable Production (X_6): This variable indicates the total income generated from vegetable farming activities, measured in million VND. Higher income suggests better financial stability, enabling farmers to invest in advanced agricultural technologies without facing significant economic constraints (Nguyễn Văn Thiệu & Nguyễn Thị Ngọc Dung, 2014).

Share of Vegetable Income in Total Household Income (X_7): This variable reflects the proportion of vegetable farming income relative to the household's total income, expressed as a percentage. Households relying more heavily on vegetable production are more likely to adopt IoT technology to increase productivity, ensure product quality, and maintain income stability.

Interest in IoT Technology (X_8): Interest in IoT technology is measured on a 5-point Likert scale, ranging from "Not interested at all" to "Very interested." Farmers with higher interest levels are more likely to adopt IoT solutions, as they perceive the technology as beneficial and compatible with their farming practices.

Access to IoT Technology (X_9): This variable represents the ease with which farmers can access IoT technology, also measured on a 5-point scale, from "Very difficult" to "Very easy." Easier access to technology, including availability, affordability, and technical support, significantly increases the likelihood of adoption.

3. Results and discussion

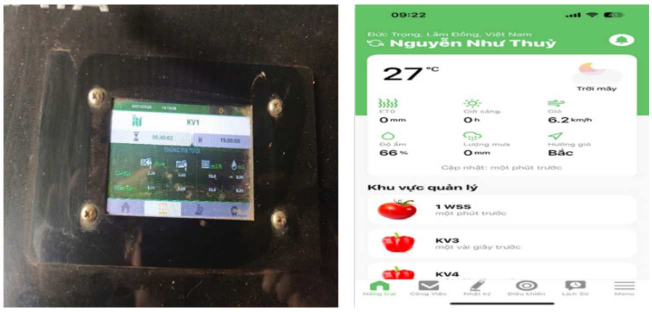
3.1. The current status of IoT adoption in vegetable production in Lam Dong province

The key IoT technologies applied in vegetable production in Lam Dong include smart sensors, automation systems, farm management software, and artificial intelligence (AI) (Figure). Among these, smart sensors play a crucial role in monitoring environmental and soil conditions. Sensors measuring humidity, air temperature, light intensity, and CO_2 concentration enable farmers to obtain real-time environmental data, allowing them to adjust cultivation conditions accordingly. Additionally, soil sensors measure pH, moisture, and temperature, helping farmers control water and fertilizer usage, thereby avoiding resource waste. Automation systems, such as drip irrigation and misting systems, are also integrated with sensors to ensure accurate and timely delivery of water and nutrients, promoting optimal crop growth.

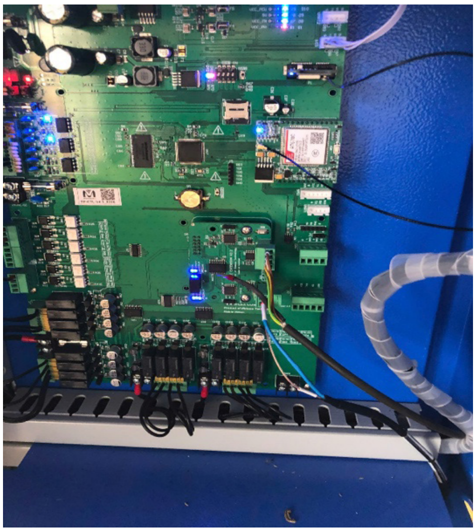
The smart farm management software connects IoT devices, allowing farmers to manage the entire production process through smartphones or computers. This system enables them to monitor environmental data, control automated devices, receive pest alerts, and plan production more efficiently. Moreover, AI systems analyze sensor data to provide recommendations for pest prevention, predict harvest times, and optimize cultivation practices.

Although the effectiveness of IoT has been proven, the initial investment required for these systems remains a significant barrier for smallholder farmers. IoT investment typically involves multiple components, including hardware, management software, network systems, and maintenance. For a 1-hectare greenhouse, sensor costs range from 2 to 5 million VND per sensor, central control units from 15 to 50 million VND, drip irrigation systems from 20 to 30 million VND per hectare, and management software with annual usage fees ranging from 10 to

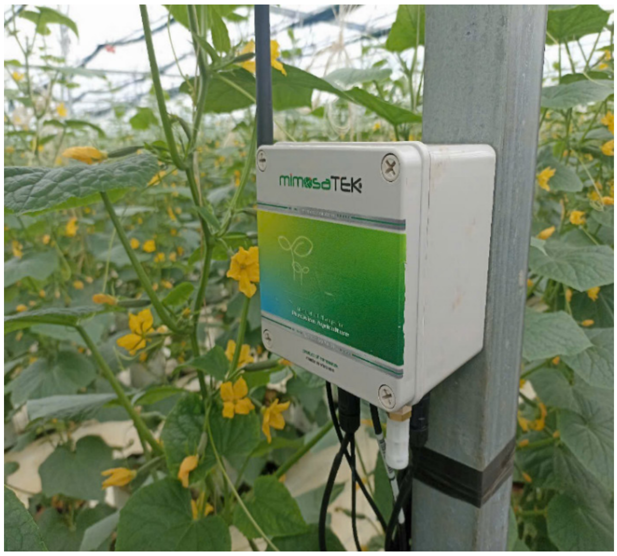
(a) Main system and automatic fertilization system



(b) Sensor on IoT device and mobile app



(c) Sensor circuit inside the machine



(d) Climate sensor in the garden

Figure 1. IoT system in vegetable farms in Lam Dong

30 million VND. Additionally, farmers must cover maintenance, network connectivity, and energy costs, bringing the total initial investment for a complete IoT system to approximately 80 to 160 million VND. However, as IoT technologies and software become more commonly produced domestically, dependence on imports has significantly decreased.

The current adoption of IoT in Lam Dong is primarily concentrated in large farms and agricultural cooperatives, covering approximately 60% of the province's greenhouse vegetable production area. However, expanding IoT adoption among smallholder farmers remains challenging, mainly due to limited investment capital and technical knowledge. To address these challenges, local authorities and businesses should implement financial support programs, such as subsidies for IoT equipment, preferential loan packages, and specialized technical training. Additionally, developing internet infrastructure and clean energy solutions in rural areas is essential to ensure the stable operation of IoT devices.

According to Table 1, among households without IoT application, the majority fall within two main categories: 47.7% have production areas ranging from 1,000 to 3,000 m², and 43.1% have areas between 3,000 and 5,000 m². Other categories include 9.2% with areas between 5,000 m² and 1 hectare, while no household has less than 1,000 m² or more than 1 hectare. In contrast, households applying IoT technology show more diverse land distribution. Among them, 44.6% have production areas between 1,000 and 3,000 m², 46.2% between 3,000 and 5,000 m², 7.7% between 5,000 m² and 1 hectare, and 1.5% with more than 1 hectare. No IoT-adopting households operate on less than 1,000 m². This indicates that IoT-adopting households tend to expand their production areas compared to non-adopting households.

The majority of households (80%, corresponding to 52 households) invested between 100 and 300 million VND in IoT equipment for vegetable production, making it the most common investment range. This shows that many households are willing to

Table 1. Vegetable Production Area of Farming Households

Vegetable Production Area	Without IoT		With IoT	
	Households (No.)	Percentage (%)	Households (No.)	Percentage (%)
Less than 1,000 m²	0	0.0	0	0.0
1,000 to 3,000 m²	31	47.7	29	44.6
3,000 to 5,000 m²	28	43.1	30	46.2
5,000 m² to 1 ha	6	9.2	5	7.7
More than 1 ha	0	0.0	1	1.5
Total	65	100	65	100

invest significantly in IoT to improve their production. Only 13.8% (9 households) invested less than 100 million VND, indicating that lower-cost investments are less common, likely due to limited efficiency or functionality of cheaper devices. Meanwhile, only 6.2% (4 households) invested more than 300 million VND, reflecting those higher investments are only feasible for households with greater financial capacity or larger production scales.

Survey data also reveal varying levels of government support for IoT investment. One household received 10–20% support, corresponding to an investment of 110 million VND, equivalent to 11 to 22 million VND in subsidies, a relatively low support level suitable for households with moderate financial capacity. Additionally, 11 households received 20–50% support, with equipment costs ranging from 104 to 324 million VND. This significant support helped reduce investment burdens, particularly for households facing higher costs, such as 324 million VND. This suggests that government support tends to focus on medium and large-scale households with greater potential for effective IoT adoption.

Furthermore, one household received 50–70% support, with an equipment cost of 94 million VND, representing the highest support level, typically provided to disadvantaged households or pilot programs promoting IoT adoption. Among the surveyed households, 8 invested less than 100 million VND, 42 invested between 100 and 300 million VND, and the remaining households investing over 300 million VND did not receive any government support. These households fully financed their IoT investments, indicating stronger financial capacity or clear recognition of the economic benefits of IoT adoption.

Overall, the current state of IoT adoption in vegetable production reflects a positive transformation, with 80% of households willing to make significant investments in IoT systems, typically ranging from 100 to 300 million VND. This investment level reflects the desire to improve productivity and product quality through modern technology. However, the data also highlight disparities in access and investment, depending on production scale, financial capacity, and government support. Some households benefited from government assistance, with subsidy rates ranging from 10% to 70%, reducing investment burdens, particularly for households with moderate financial capacity or larger production scales. Nevertheless, most households (62 households) did not receive any support and had to fully self-finance their IoT investments. This indicates that while IoT is gradually gaining acceptance due to its long-term economic benefits, significant barriers remain for smallholder farmers with limited resources. To further expand IoT adoption, additional support policies are needed, especially for households facing financial challenges, ensuring equitable and sustainable technology adoption.

Table 2. Sources of IoT Information for Vegetable Farmers

Information Source	Households (No.)	Percentage (%)
Unaware of IoT	15	11.6
Relatives and neighbors	64	49.2
Traders and collectors	14	10.8
TV, phones (internet)	28	21.5
Agricultural extension staff	9	6.9
Total	130	100

Vegetable farmers primarily access IoT information through community networks (Table 2), with 49.2% of households relying on relatives and neighbors, highlighting the importance of social relationships in information dissemination. Media channels such as TV, mobile phones, and the internet account for 21.5%, while traders and collectors represent only 10.8%. Notably, the role of agricultural extension staff is limited, accounting for just 6.9%, indicating that extension activities have not been particularly effective in promoting IoT awareness. Furthermore, 11.6% of households remain unaware of IoT technology, reflecting gaps in information access or challenges in outreach. Therefore, it is essential to strengthen official communication channels and enhance the role of agricultural extension services to improve farmers' awareness and access to IoT technology.

3.2. Factors Influencing the Decision to Apply IoT Technology in Vegetable Production

The descriptive statistics table (Table 3) shows data from 130 complete observations with no missing values. The variables exhibit variations in mean values, standard deviations, and dispersion levels.

Table 4 shows that variables X_1 (Age), X_4 (Cultivated Area), X_5 (Investment Capital), and X6 (Vegetable Income) have p-values greater than 0.1, indicating no statistically significant relationship between these variables and the likelihood of IoT adoption in vegetable production.

Conversely, the following variables show statistically significant relationships with IoT adoption: Education Level (X_2): Positive correlation with the dependent variable. Higher education levels increase the likelihood of adopting IoT technology. Farming Experience (X_3): Positive correlation with the dependent variable. Farmers with more experience are more likely to adopt IoT. Share of Vegetable Income (X_7): Positive correlation with the dependent variable. The higher the proportion of vegetable income, the more likely farmers adopt IoT. Interest in IoT (X_8): Strong positive correlation. Higher interest in IoT significantly increases the likelihood of adoption. Access to IoT (X_9): Positive correlation. Easier access to IoT increases the likelihood of adoption as farmers become more aware of its benefits.

The model fit test results show that the Chi-square statistic for Step 1, Block, and Model is 144.734, with a p-value (Sig.) = 0.000. Since the p-value is less than 0.1, the overall model demonstrates a statistically significant relationship between the dependent variable and the independent variables at a confidence level of over 99%.

The model's explanatory power, as measured by Nagelkerke R^2, is 0.895, indicating that 89.5% of the variation in the dependent variable (IoT adoption) can be explained by the independent variables included in the model. This suggests that the model is relatively robust and provides meaningful statistical insights.

The prediction accuracy test shows the model's ability to distinguish between households adopting IoT (Y=1) and those not adopting IoT (Y=0).

For non-adopting households (Y=0), the model correctly predicted 62 out of 65 cases (95.4% accuracy), with only 3 misclassified cases (4.6% error rate).

Table 3. Descriptive Statistics of Variables

Variable	N	Minimum Value	Maximum Value	Mean Value	Standard Deviation
X_1 (Age)		22	65	40.81	11.047
X_2 (Education Level)		2	14	8.01	3.443
X_3 (Farming Experience)		2	35	9.55	5.800
X_4 (Cultivated Area)		2	30	7.74	4.807
X_5 (Investment Capital)	130	-13	640	132.19	114.080
X_6 (Vegetable Income)		33	920	240.42	166.744
X_7 (Share of Vegetable Income)		40	100	72.22	19.261
X_8 (Interest in IoT)		1	5	3.06	1.055
X_9 (Access to IoT)		1	5	2.36	1.155

Table 4. Regression Model Output

Variables in the Model	Estimated Coefficient (β)	Standard Error (S.E.)	Odds Ratio (E^(β))
X_1 (Age)	0.011^{ns}	0.049	1.011
X_2 (Education Level)	0.380^{**}	0.185	1.462
X_3 (Farming Experience)	0.379^{***}	0.121	1.460
X_4 (Cultivated Area)	-0.049^{ns}	0.166	0.952
X_5 (Investment Capital)	0.000^{ns}	0.011	1.000
X_6 (Vegetable Income)	-0.007^{ns}	0.006	0.993
X_7 (Share of Vegetable Income)	0.047^{*}	0.026	1.049
X_8 (Interest in IoT)	4.423^{***}	1.226	83.329
X_9 (Access to IoT)	2.481^{***}	0.774	11.959
Constant	-27.030	6.986	0.000

*Note: *, **, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.*

For IoT-adopting households (Y=1), the model correctly predicted 61 out of 65 cases (93.8% accuracy), with 4 misclassified cases (6.2% error rate).

Marginal effects analysis

Assuming an initial probability P_0=10%.

a) Education Level (X_2) (β_2 = 0.380; P_0 = 10% and $e^{\beta 2}$ = 1.462)

$$P_2 = \frac{P_0 \times e^{\beta_2}}{1 - P_0(1 - e^{\beta_2})} = \frac{0.1 \times 1.462}{1 - 0.1(1 - 1.462)} = 0.14$$

If the initial probability of adopting IoT is 10%, an increase in education level by one year, while holding other factors constant, raises the adoption probability to 14%, reflecting a 4% increase from the initial probability.

b) Farming Experience (X_3) (β_3 = 0.379; P_0 = 10%, and $e^{\beta 3}$ = 1.460)

$$P_3 = \frac{P_0 \times e^{\beta_3}}{1 - P_0(1 - e^{\beta_3})} = \frac{0.1 \times 1.460}{1 - 0.1(1 - 1.460)} = 0.14$$

For farmers with increased farming experience, the probability of IoT adoption rises from 10% to 14%, reflecting a 4% increase compared to the initial probability.

c) Share of Vegetable Income (X_7) (β_7 = 0.047; P_0 = 10%, and $e^{\beta 7}$ = 1.049)

$$P_7 = \frac{P_0 \times e^{\beta_7}}{1 - P_0(1 - e^{\beta_7})} = \frac{0.1 \times 1.469}{1 - 0.1(1 - 1.469)} = 0.104$$

For households with a higher share of vegetable income in their total income, the probability of IoT adoption increases from 10% to 10.4%, showing a 0.4% increase compared to the initial probability.

d) Interest in IoT (X_8) (β_8 = 4.423; P_0 = 10%, and $e^{\beta 8}$ = 83.329)

$$P_8 = \frac{P_0 \times e^{\beta_8}}{1 - P_0(1 - e^{\beta_8})} = \frac{0.1 \times 83.329}{1 - 0.1(1 - 83.329)} = 0.902$$

Farmers with higher interest in IoT technology see their adoption probability increase from 10% to 90%, reflecting a significant 80% increase compared to the initial probability.

e) Access to IoT (X_9) (β_9 = 2.481; P_0 = 10%, and $e^{\beta 9}$ = 11.959)

$$P_9 = \frac{P_0 \times e^{\beta_9}}{1 - P_0(1 - e^{\beta_9})} = \frac{0.1 \times 11.959}{1 - 0.1(1 - 11.959)} = 0.57$$

With increased access to IoT technology, the adoption probability rises from 10% to 57%, representing a 47% increase from the initial probability.

3.3. Discussion

Education level and farming experience both exhibit positive and significant relationships with IoT adoption. Farmers with higher education levels are more likely to understand and adopt advanced agricultural technologies. This finding aligns with the study by Võ Văn Tuấn and Lê Cảnh Dũng (2015), who found that education positively influences technology adoption among Vietnamese farmers. Similarly, the significant impact of farming experience corroborates findings by Nguyễn Tuấn Kiệt and Nguyễn Tấn Phát (2019) and Nam et al. (2021), who reported that experienced farmers are more likely to perceive the benefits of smart agriculture practices, including IoT.

The positive association between the share of vegetable income and IoT adoption suggests that farmers who rely more on vegetable production are more motivated to invest in technology to enhance productivity and income stability. This aligns with findings by Abi et al. (2024), who highlighted that farmers engaged in specialized crop production are more likely to adopt IoT solutions due to their potential to optimize yields and reduce resource wastage.

The study identifies farmers' interest in IoT and access to technology as the most influential factors driving adoption. A high level of interest increases the likelihood of adoption by 80%, while easier access enhances adoption by 47%. These findings align with prior studies that emphasized that farmers' willingness to adopt IoT is strongly influenced by their perceived usefulness and ease of access (Hoàng Hà Anh et al., 2021; Anand Kumar, 2024; Duguma & Bai, 2024). Moreover, Nofriyanti and Hipma (2024) highlighted the need for adequate infrastructure and training to facilitate widespread IoT adoption.

In contrast, variables such as age, cultivated area, investment capital, and household vegetable income were not statistically significant. This finding differs from some previous studies, such as Balakrishnan et al. (2024), who reported a significant link between farm size and IoT adoption. The lack of significance in this study may reflect the unique context of Lam Dong, where even small-scale farms adopt IoT if they perceive tangible benefits, regardless of land size or income level.

The study's findings are consistent with national trends reported by MARD (2022), which indicated that IoT adoption in Vietnamese agriculture is primarily driven by education, interest, and access. Internationally studies also found that technological awareness, training, and access to infrastructure significantly enhance IoT adoption among farmers in developing regions (Al-Tulaibawi et al., 2024; Bhor et al., 2025).

4. Conclusion and recommendation

The study has highlighted the key factors influencing the adoption of IoT technologies among vegetable farmers in Lam Dong province, Vietnam. Through logistic regression analysis, the results revealed that education level, farming experience, share of vegetable income, interest in IoT, and access to IoT resources significantly impact farmers' decisions to adopt these technologies. Farmers with higher education and extensive farming experience were more likely to embrace IoT solutions, reflecting their ability to comprehend and implement advanced agricultural practices. Additionally, households with a higher proportion of income derived from vegetable farming demonstrated a greater inclination toward IoT adoption, driven by the need to enhance productivity and income stability. Among all factors, interest in IoT and ease of access emerged as the most influential determinants, emphasizing the importance of awareness and infrastructure in promoting technological adoption. Conversely, variables such as age, land size, investment capital, and overall household income were not significant predictors, indicating that IoT adoption is more closely linked to farmers' technological engagement and accessibility rather than their economic standing. These findings align with previous studies, both locally and globally, underscoring the relevance of education, access, and motivation in driving IoT adoption in agriculture. Despite the promising trends observed, barriers such as high initial investment costs, limited technical knowledge, and inadequate infrastructure still hinder widespread adoption, particularly among smallholder farmers. Addressing these challenges is crucial to ensuring equitable access to IoT technology and maximizing its potential benefits for sustainable agricultural development.

To promote the adoption of IoT technologies among vegetable farmers in Lam Dong province, several practical recommendations can be implemented. First, enhancing education and technical training is crucial. Farmers often face challenges in understanding and utilizing IoT systems due to limited technical knowledge. Therefore, regular training programs, workshops, and hands-on demonstrations should be organized to equip farmers with the necessary skills and understanding of IoT applications. Collaboration between agricultural extension services, universities, and technology providers can ensure that training materials are tailored to farmers' specific needs and local agricultural practices. Second, improving access to IoT infrastructure is equally important. Many rural areas still lack stable internet connectivity, hindering farmers from fully leveraging IoT solutions. To address this, the government, private sector, and technology providers should collaborate to expand digital infrastructure in agricultural regions. Ensuring reliable internet access would empower farmers to adopt and effectively use IoT technologies, facilitating real-time monitoring and decision-making in vegetable production. Third, financial support and incentives can also play a vital role in encouraging adoption. High initial investment costs remain a significant barrier for many farmers. To overcome this challenge, the government should introduce subsidies, low-interest loans, and cost-sharing initiatives for IoT equipment and installation. Providing financial incentives would not only reduce the economic burden but also increase farmers' willingness to invest in advanced agricultural technologies. Fourth, raising awareness and establishing demonstration projects can further drive IoT adoption. Awareness campaigns highlighting the benefits of IoT in improving productivity, resource efficiency, and profitability can inspire farmers to explore these technologies. Setting up pilot projects and model farms showcasing successful IoT implementation can demonstrate the tangible benefits and encourage farmers to adopt similar practices on their own farms. Fifth, strengthening agricultural extension services is another key recommendation. Extension officers should be equipped with IoT-related knowledge and resources to provide farmers with practical guidance and ongoing support. Integrating IoT education into existing agricultural extension programs can ensure that farmers remain informed about the latest technological advancements and best practices. Finally, fostering collaboration among stakeholders can further accelerate IoT adoption. Partnerships between farmers, agricultural cooperatives, technology providers, and research institutions can promote knowledge exchange, innovation, and the development of locally adapted IoT solutions. By encouraging collaborative efforts, policymakers can ensure that IoT technologies are not only accessible but also customized to address the specific needs and challenges faced by vegetable farmers in Lam Dong province.

While this study provides valuable insights into the factors influencing IoT adoption among vegetable farmers in Lam Dong province, several limitations should be acknowledged. First, the research relies on cross-sectional survey data, which may not fully capture changes in farmers' behaviors or attitudes over time. Second, the study focuses on two specific vegetable crops—tomatoes and bell peppers—which may limit the generalizability of the findings to other crop types. Future research could address these limitations by employing longitudinal data to analyze trends over time, expanding the scope to include a wider variety of crops and farming systems, and incorporating qualitative methods (e.g., in-depth interviews or focus groups) to explore farmers' perceptions and barriers in more detail. Additionally, comparative studies between provinces or regions with different levels of IoT integration could provide broader policy implications for smart agriculture development in Vietnam and beyond.

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