



## Logistic Regression Analysis of Factors Influencing Mobile Application Adoption in Smallholder Livestock Farming: A Case Study from Northern Thailand

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### ABSTRACT

This study examines the factors affecting the adoption of mobile farming management applications by smallholder livestock farmers in Northern Thailand. Data from 300 farmers were analyzed using binary logistic regression to evaluate 14 independent variables and their influence on application use. Four significant factors were identified: education level, participation in training programs, extension support, and membership in farmer associations. Education and participation in training programs were highly significant ( $p < 0.001$ ), whereas extension support and membership in farmer associations were both significantly associated with mobile application use ( $p < 0.01$  and  $p < 0.05$ ). Our findings indicate that educational initiatives, training programs, and strong extension support are crucial in enhancing mobile application adoption. Farmer associations also play a vital role in promoting technology use through peer influence and social networks. These insights highlight the importance of targeted strategies to improve mobile application adoption, thereby contributing to more efficient livestock management practices. To create practical and long-term digital solutions specifically designed to meet smallholder farmers' requirements, it is essential to gain an in-depth understanding of these elements. The findings highlight the importance of addressing educational gaps, promoting training programs, and enhancing extension services to encourage technology adoption among smallholder farmers. By focusing on these critical factors, farmers can increase their adoption of mobile applications, thereby improving livestock management efficiency and enhancing the adaptability of smallholder farming systems in rural areas.

**Keywords:** *adoption; farm management; logistic regression; mobile application; smallholder farmers*

### INTRODUCTION

Smallholder farmers play a significant role in the agricultural sectors of developing countries, particularly Thailand. According to the World Bank, 70%, 23%, and 6% of rural households with farms are small, medium, and large holders, respectively (The World Bank, 2020). Smallholder farmers are key producers in the livestock sector and are primarily responsible for cattle and buffalo production. They often employ mixed agricultural systems that integrate crop cultivation and livestock farming. Beef cattle and buffalo are significant in Northern Thailand's livestock sector, contributing to the region's cultural and economic development. Despite their importance, small-scale farmers face challenges such as competitiveness and limited access to information, resources, and modern technologies, limiting their productivity and profitability (Balehegn *et al.*, 2020; Ifeoma *et al.*, 2021).

Integrating digital technology into agriculture, mainly through mobile applications, revolutionizes global farm management practices. Advancements in the Internet of Things (IoT), artificial intelligence (AI),

big data analytics, and other digital tools are driving this transformation, enhancing productivity, sustainability, and decision-making in agriculture (Baseca *et al.*, 2019; Nasirahmadi & Hensel, 2022; Navulur *et al.*, 2017). These technologies, part of the broader smart farming or Agriculture 4.0 movement, enhance efficiency and sustainability. Numerous mobile applications have been developed to assist in livestock management, especially for operations such as recording animal identification information, managing breeding, providing vaccinations and deworming, monitoring feed intake and animal health, and enabling sales (Batla *et al.*, 2023). In addition, applications can provide early disease diagnosis, record behavioral patterns, access real-time market prices and information, deliver extension services, and offer real-time weather updates and community knowledge sharing among farmers (Junior *et al.*, 2021; Mohanty *et al.*, 2024; Shanka & Genale, 2022).

Several mobile applications have been developed to enhance livestock management. For example, FarmDain is web-based and has been shown to improve decision-making in dairy sheep and goat farming, resulting

in more effective farm performance and profitability (Louta *et al.*, 2023). An additional mobile application called “The Taurus” uses machine learning to identify cattle breeds and diseases, provide solutions, and suggest preventive methods (Chandrarathna *et al.*, 2022).

The adoption of mobile applications for livestock farm management is becoming increasingly important in the agricultural sector. Numerous demographic characteristics, including age, education, income and farming revenue, farming experience, membership in agricultural groups, and animal ownership, significantly influence the adoption and use of mobile applications for livestock production. According to Barrios *et al.* (2023) and Triatmojo *et al.* (2024), these factors significantly influence the adoption and use of mobile applications for livestock production.

Understanding the factors affecting smallholder participation in farm management mobile application services is essential to developing effective and sustainable solutions adapted to specific requirements and situations. This study aimed to identify and analyze the key factors influencing mobile application adoption for livestock management among small-scale farmers in Northern Thailand. Specifically, it analyzed the influence of sociodemographic characteristics, farm characteristics, smartphone and Internet use, and training and support characteristics.

## MATERIALS AND METHODS

### Study Area

This study was conducted in the Northern Thai provinces of Phayao and Chiang Rai (Figure 1). These provinces were selected because of their significant role in the Northern Thailand livestock sector as well as their active participation and collaboration with the Department of Livestock Development (DLD) and local farmer cooperatives. This includes the direct involvement of farmers in partnership with the research team, which facilitated the development of targeted training programs and promoted the adoption of mobile applications for farm management. The collaborations have resulted in the development of comprehensive training courses that focus on smallholder farmers’ use of mobile applications. For sustainable livestock sector development, farmers’ perspectives on mobile applications for beef cattle and buffalo farm management are essential.

### Data Collection

The research protocol was approved by the University of Phayao Human Ethics Committee (approval number: HREC-UP-HSST 1.2/156/66). Following this approval, we began collecting information. All participants were informed of the important aspects of the study, including the data collection process, privacy, and confidentiality considerations. All participants signed a consent form before participating in the study. Data were collected through a household survey from October 2023 to September 2024. Personal data and farm details were

collected through in-person interviews with 300 farmers. The purposive sampling method was used to select a specific group of farmers, consisting of 300 respondents who were members of the livestock farmer group. The questionnaire used a mix of multiple-choice and open-ended questions to gather information, including sociodemographic information, farm characteristics, smartphone use, training programs, and support characteristics.

### Description of Variables

We hypothesized that sociodemographic, farm, smartphone and internet use, as well as training and support characteristics, primarily influence farmers’ adoption of mobile applications. In the present investigation, we categorized one dependent variable as either “user” or “non-user” regarding livestock farm management mobile applications. To simplify the discussion and evaluation of the influence of the independent variables on mobile device application adoption, this study categorized them into four groups (Table 1).

### Data Analysis

Logistic regression is a method used to analyze the association of categorical or continuous independent variables with one dichotomous dependent variable (Baba *et al.*, 2019; Szafraniec-Siluta *et al.*, 2022; Yuniarsih *et al.*, 2024). To discover the influence of farm characteristics on mobile application use, this study analyzed the different farm characteristics (categorical independent variables) and mobile application utilization (dependent variable) using binary logistic regression. Data were collected from 300 farmers using a questionnaire. These data were then transformed into appropriate formats and categories before data analysis. For example, continuous values, such as age, household income, and farm experience, were transformed into a nominal scale before processing in SPSS. The total number and percentage of patients in each group were calculated using descriptive statistics. The relationships between the variables were analyzed using the Chi-square test. Binary logistic regression was used to identify a significant effect between the dependent variable and a set of independent variables. The Wald test values from a binary logistic regression showed the important independent variables that have a significant effect on livestock application software utilization, which was the dependent variable. The prediction accuracy of the binary logistic regression model was further compared with that of other widely used prediction models: deep learning, random forest, and k-nearest neighbors (KNN). The prediction accuracy values of all models were computed using the RapidMiner tool.

The dependent variable was the opportunity to utilize livestock application software. The value of the dependent variable was set to 1 if a farmer used application software and 0 if it was not used. Because the dependent variable was a dummy variable that consisted of two statuses (0 or 1), a binary logistic

Table 1. Definition and measurement of sociodemographic variables among respondent farmers for analyzing mobile application adoption

Variables	Description
<b>Sociodemographic Characteristics</b>	
Age	The age groups were divided into four categories: 1= youth ( $\leq 20$ years), 2= young adults (21–40 years), 3= middle-aged (41–60 years), and 4= older adults (>60 years). The year of birth determines the age in 2023.
Gender	This variable assigned codes to indicate the gender of males= 0 and females= 1.
Education	This variable categorizes individuals based on their level of education: 1= no formal education, 2= primary education, 3= secondary education, and 4= bachelor's degree or higher.
Household size	The number of family members was classified as follows: 1= small size (1–3 members), 2= medium (4–6 members), and 3= large (>6 members).
Household income	Annual household income was categorized into the following ranges: 1= below 50,000 baht/year, 2= 50,000–100,000 baht/year, 3= 100,001–150,000 baht/year, and 4= >150,000 baht/year.
<b>Farm Characteristics</b>	
Farm experience	The duration of the farming experience was classified into the following intervals: 1= <1 year, 2= 1–3 years, 3= 4–6 years, 4= 7–10 years, and 5= >10 years.
Farm size	Animals on the farm were categorized into four groups according to their head total: 1= 1–5 heads, 2= 6–10 heads, 3= 11–15 heads, and 4= >15 heads.
Farming system	The farm system was categorized into 3 groups: 1= extensive, 2= semi-intensive, and 3= intensive.
<b>Smartphone and Internet Use Characteristics</b>	
Internet access	Internet access refers to the ability of the respondent to create an online connection with the Internet as follows: 0= no Internet access and 1= having Internet access.
Package service	Mobile package services can be classified as prepaid= 0 and post-paid= 1.
Internet use	The variable Internet use is classified into four levels according to daily use, as follows: 1= no internet use, 2= low (<1 hour/day), 3= medium (1–3 hours/day), and 4= high (>3 hours/day).
<b>Training and Support Characteristics</b>	
Participation in training programs	This variable indicates whether the respondent attended any training program involving technological use, farming practices, or other related topics. The response is denoted as follows: 0= No, which indicates “has not received training” and 1= Yes, which indicates “has received training.”
Membership of association	This variable asks whether the respondent is a member of any farmers' cooperative or farmers' group: 0= No and 1= Yes.
Extension support	This variable indicated whether the respondent received extension support, which consisted of providing resources, advice, and knowledge to farmers to enhance their agricultural practices and overall efficiency. 0= No (not receiving assistance from extension services) and 1= Yes (receiving assistance from extension services).

regression model was used to analyze the data in this study. The binary logistic regression model was computed as follows:

$$L_k = \ln [P_k / (1 - P_k)] = b_0 + b_1X_1 + b_2X_2 + \dots + b_nX_n$$

where  $P_k$  is the probability of using the livestock mobile application;  $1 - P_k$  is the probability of the non-use livestock mobile application;  $b_0$  is an intercept;  $b_1$  is regression coefficient ( $i = 1, 2, 3, \dots, n$ );  $X_1$  is age;  $X_2$  is gender;  $X_3$  is education level;  $X_4$  is household size;  $X_5$  is household income;  $X_6$  is farm experience;  $X_7$  is farm size;  $X_8$  is farming system;  $X_9$  is access to the internet;  $X_{10}$  is package service;  $X_{11}$  is Internet use;  $X_{12}$  is participation in training programs;  $X_{13}$  is membership of an association; and  $X_{14}$  is extension support.

## RESULTS

### Overall Summary of Variables

Table 2 presents descriptive information for the variables used in the present study. Summary statistics showed that the surveyed farmers had an average age of 55 years. Males constituted the majority, accounting for 75.67% of the total, three times higher than the propor-

tion of females (24.33%). In terms of education, most farmers had a primary education (55.33%), followed by a secondary education (28.33%), bachelor's degree or higher (12.33%), and no formal education (4.00%). The distribution of household income was comparatively even, with 31.00% of households with an income less than 50,000 baht/year, 30.67% with an income between 50,001 and 100,000 baht/year, 22.33% with an income more than 150,000 baht/year, and 16.00% with an income between 100,001 and 150,000 baht/year. The household size distribution showed that medium (4–6 members) and small households (1–3 members) accounted for a similar proportion of 48.00%, while large households (>6 members) accounted for only 4.00%.

Regarding farm experience, the majority of farmers had 4–6 years of experience (28.33%), followed closely by 1–3 years (28.00%). In terms of farming systems, semi-intensive farming was the most common (54.33%), followed by intensive (28.33%) and extensive (17.33%) farming systems. When considering farm sizes based on the number of livestock farms, farms with 1–5 heads represented 44.67% of the distribution. Farms with more than 15 heads accounted for 22.67%, and those with 6–10 heads accounted for 18.00%. Of the farms, 14.67% had 11–15 heads.

Among those with Internet access, 43.00% reported low internet use (<1 h/day), and 29.00% reported moderate use (1–3 h/day). Only 5.00% reported high use (>3 h/day). Regarding package services, a significant majority (71.00%) used prepaid services, whereas 29.00% used postpaid services.

Participation in training programs was relatively high, with 65.00% of farmers indicating that they participated in such programs compared to 35.00% who

did not. Association membership was split, with 61.33% of farmers being association members and 38.67% not being members. Extension support was widely accessed, with 84.33% of farmers receiving extension support and only 15.67% not receiving such support.

Table 2. Summary of survey data on dependent and independent variables among respondent farmers for mobile application usage (N=300)

Variables	Measurement	N (300)	%
<b>Dependent variables</b>			
UseApp	0 = Non-user	163	54.33
	1 = User	137	45.67
<b>Independent variables</b>			
Age	1 = <20 years old	2	0.67
	2 = 21–40 years old	23	7.67
	3 = 41–60 years old	187	62.33
	4 = >60 years old	88	29.33
Gender	0 = Male	73	24.33
	1 = Female	227	75.67
Educ	1 = No formal education	12	4.00
	2 = Primary education	166	55.33
	3 = Secondary education	85	28.33
	4 = Bachelor's degree or higher	37	12.33
HouseSi	1 = Small	144	48.00
	2 = Medium	144	48.00
	3 = Large	12	4.00
HouseIn	1 = <50,000 baht/year	93	31.00
	2 = 50,00–100,000 baht/year	92	30.67
	3 = 100,001–150,000 baht/year	48	16.00
	4 = >150,000 baht/year	67	22.33
FarmExp	1 = <1 year	29	9.67
	2 = 1–3 years	84	28.00
	3 = 4–6 years	85	28.33
	4 = 7–10 years	20	6.67
	5 = >10 years	82	27.33
FarmSi	1 = 1–5 heads	134	44.67
	2 = 6–10 heads	54	18.00
	3 = 11–15 heads	44	14.67
	4 = >15 heads	68	22.67
FarmSys	1 = Extensive	52	17.33
	2 = Semi-intensive	163	54.33
	3 = Intensive	85	28.33
InternetAcc	0 = No	69	23.00
	1 = Yes	231	77.00
Package	0 = Prepaid	213	71.00
	1 = Post-paid	87	29.00
InternetUse	1 = No	69	23.00
	2 = Low	129	43.00
	3 = Medium	87	29.00
	4 = High	15	5.00
ParTrain	0 = No	105	35.00
	1 = Yes	195	65.00
Member	0 = No	116	38.67
	1 = Yes	184	61.33
ExtenSup	0 = No	47	15.67
	1 = Yes	253	84.33

Source: own elaboration, 2024.

**Model Accuracy Test**

The behavior of farmers applying farm management application software to support their farms was further predicted using four models: logistic regression, KNN, random forest, and deep learning. These prediction models were used to analyze the correlation between farming factors (independent variables) and application software use (dependent variable) for farm management. All 14 features of farms from 300 cases were fed into the model as independent variables, and application utilization (use, non-use) was defined as a dependent variable in the model. Table 3 shows the overall accuracy of the four prediction models in predicting application use by farmers. The logistic regression and deep learning models performed better than the random forest and KNN models. The logistic regression model yielded the highest overall prediction accuracy (86.67%), indicating that the logistic regression model is appropriate for analyzing the correlation between farm properties and application utilization.

**Relationship between Variables**

Table 4 presents the relationships between variables and farm management applications using chi-square tests of independence. It displays the frequencies and percentages of users and non-users across variable categories. There was a statistical association between age and farm management application use ( $\chi^2=14.889$ ,  $p=0.002$ ), indicating differences in adoption across age groups, with higher use in the 41–60 age group. Young adults (21–40) and middle-aged users (41–60) showed higher application use than older adults (>60 years). Education level was significantly associated with applying application software ( $\chi^2=58.365$ ,  $p<0.001$ ), with higher use among more educated individuals. Higher educational levels correlated with higher application use. The household income level also showed a statistical association with application use ( $\chi^2=22.602$ ,  $p<0.001$ ), with higher use among those with incomes between 50,001 and 100,000 (baht/year), indicating that economic factors influence application adoption. A higher household income was associated with application software utilization. The type of farm system was significantly associated with application use ( $\chi^2=20.805$ ,  $p<0.001$ ),

Table 3. Comparison of prediction accuracy among four models for mobile application adoption

Model	Accuracy
Logistic Regression	86.67%
Deep Learning	85.67%
Random Forest	85.33%
K-Nearest Neighbors	79.67%

Table 4. Analysis of the relationship between variables and livestock mobile application adoption among farmers

Variables	Non-user		User		Total		Chi-square	df	p-value	
	N	%	N	%	N	%				
Age (year)	<20	1	0.33	1	0.33	2	0.67	14.889	3	0.002
	21–40	6	2.00	17	5.67	23	7.67			
	41–60	96	32.00	91	30.33	187	62.33			
	>60	60	20.00	28	9.33	88	29.33			
Education	Not educated	12	4.00	0	0.00	12	4.00	58.365	3	0.000
	Primary education	108	36.00	58	19.33	166	55.33			
	Secondary education	42	14.00	43	14.33	85	28.33			
	Bachelor's degree or higher	1	0.33	36	12.00	37	12.33			
Household income (baht/year)	<50,000	68	22.67	25	8.33	93	31.00	22.602	3	0.000
	50,001–100,000	42	14.00	50	16.67	92	30.67			
	100,001–150,000	27	9.00	21	7.00	48	16.00			
	>150,000	26	8.67	41	13.67	67	22.33			
Farm system	Extensive	38	12.67	14	4.67	52	17.33	20.805	2	0.000
	Semi-intensive	95	31.67	68	22.67	163	54.33			
	Intensive	30	10.00	55	18.33	85	28.33			
Internet access	No	69	23.00	0	0.00	69	23.00	75.317	1	0.000
	Yes	94	31.33	137	45.67	231	77.00			
Participation in training programs	No	94	31.33	11	3.67	105	35.00	80.623	1	0.000
	Yes	69	23.00	126	42.00	195	65.00			
Membership of association	No	100	33.33	16	5.33	116	38.67	77.439	1	0.000
	Yes	63	21.00	121	40.33	184	61.33			
Extension support	No	33	11.00	14	4.67	47	15.67	5.664	1	0.017
	Yes	130	43.33	123	41.00	253	84.33			
Phone type	Feature phone	69	23.00	0	0.00	69	23.00	75.317	1	0.000
	Smartphone	94	31.33	137	45.67	231	77.00			
Internet use (hour/day)	No	69	23.00	0	0.00	69	23.00	75.770	3	0.000
	Low (<1)	52	17.33	77	25.67	129	43.00			
	Medium (1–3)	37	12.33	50	16.67	87	29.00			
	High (>3)	5	1.67	10	3.33	15	5.00			

with higher use in semi-intensive and intensive systems. Users involved in semi-intensive and intensive farming use farm management software. Internet access ( $\chi^2=75.317$ ,  $p<0.001$ ), participation in training ( $\chi^2=80.623$ ,  $p<0.001$ ), membership in associations ( $\chi^2=77.439$ ,  $p<0.001$ ), and extension support ( $\chi^2=5.664$ ,  $p=0.017$ ) were also significantly associated with application adoption. The phone type (feature phone vs. smartphone) showed a significant relationship ( $\chi^2=75.317$ ,  $p<0.001$ ). Internet access is crucial for application use. There was a strong correlation between participation in training programs and application use. Being a member of an association was significantly related to application use. Extension support was significantly associated with application use but less strongly associated with other factors. Internet use duration exhibited a highly significant association ( $\chi^2=75.770$ ,  $p<0.001$ ) with higher use among those with medium (1–3 hours/day) and high (>3 hours/day) Internet use. More Internet use hours were correlated with higher application use.

#### Influence of Variables in Application Program Utilization

The results of the logistic regression model, as shown in Table 5, demonstrated that farmer education,

participation in training programs, membership in associations, and extension support significantly affected the utilization of farm management application software. A significant positive correlation ( $p<0.001$ ) was observed between farmer education and software utilization, indicating that farmers with higher education levels were more inclined to use applications for farm management systems. Similarly, a significant positive relationship ( $p<0.001$ ) existed between participation in training programs and application use, as training provides farmers with more opportunities to benefit from software. Furthermore, membership in associations showed a significant positive relationship ( $p<0.02$ ) with application utilization, suggesting that association members had greater access to these tools. Additionally, extension support exhibited a positive relationship ( $p<0.01$ ) with software adoption, indicating that farmers receiving support integrated application programs into their farm management practices.

#### DISCUSSION

This study examined the factors associated with farm management applications among smallholder farmers. The adoption of such applications by small-scale livestock farmers in Thailand has not yet been the

Table 5. Logistic regression analysis of factors influencing livestock mobile application adoption

Variables	B	SE	Wald	P-value	Exp(B)
Gender	0.230	0.516	0.199	0.655	1.259
Age	-0.652	0.405	2.584	0.108	0.521
Educ	1.393	0.360	14.946	0.000***	4.029
HouseSi	-0.429	0.387	1.229	0.268	0.651
HouseIn	0.056	0.191	0.086	0.770	1.057
FarmSi	-0.252	0.185	1.842	0.175	0.778
FarmSys	0.439	0.416	1.112	0.292	1.551
FarmExp	0.268	0.173	2.411	0.120	1.307
InternetAss	21.656	4132.286	0.000	0.996	2542053810.781
ParTrain	2.530	0.681	13.801	0.000***	12.555
Member	1.459	0.628	5.389	0.020**	4.300
ExtenSup	1.611	0.625	6.649	0.010**	5.008
Package	-0.594	0.437	1.852	0.174	0.552
InternetUse	-0.096	0.357	0.072	0.789	0.909
Constant	-27.237	4132.287	0.000	0.995	0.000

Note: \*\*\* and \*\*, Significant at  $p < 0.001$  and  $p < 0.05$  respectively. B, Parameter estimate; SE, Standard error.

subject of research. This study used a binary logistic regression model to evaluate the variables influencing smallholder farmers' adoption of mobile applications.

For educational level, the model showed a significant positive relationship ( $p < 0.001$ ) between education level and the probability of mobile application use (Table 5). This implies that educated farmers were more likely to utilize mobile applications. The value of Exp(B), which is more than 1, can represent if the education level increases by 1 category level, then the ratio of the possibility of mobile application use increases by a factor of 4.03, assuming the other independent variables are constant. Consistent with research conducted in Tunisia, Egypt, and Myanmar, education level plays a significant role in influencing farmers' adoption and use of mobile phone applications (Dhraief *et al.*, 2019; Mansour, 2022; Thar *et al.*, 2021). This finding suggests that a higher level of education enhances farmers' likelihood of adopting mobile applications, as primary education significantly influences use. Digital literacy training, on-farm demonstrations, and continuous support services enhance user confidence and maintain engagement. The demonstration of immediate benefits enhances the adoption and development of mobile applications as essential tools for smallholder farmers (Kambale *et al.*, 2024).

The model revealed a significant positive relationship ( $p < 0.001$ ) between participation in a training program and the probability of mobile application use. The Exp(B) or odds ratio value shows that if the participation in a training program increases by one unit, then the ratio of the possibility of mobile application use increases by 12.56 times, assuming the other independent variables are constant. Palacpac *et al.* (2024) demonstrated that the KBGAN iHealth© and KBGAN iFeed© applications optimized buffalo management in the Philippines by providing precise health diagnostics, feeding recommendations, and data management tools. These features enable agricultural extension professionals to enhance delivery services and improve buffalo farmers' decision-making. Moreover,

Saengwong *et al.* (2021) emphasized the importance of training initiatives to improve farmers' understanding of emerging technologies, further supporting efforts to enhance farm productivity. Integrating training programs with mobile applications allows farmers access to valuable information, monitors livestock health, and makes informed decisions, improving management practices and increasing efficiency in the livestock sector. Therefore, active participation in training programs facilitates the adoption and effective utilization of mobile applications for livestock farming, benefiting farmers and the entire industry.

We observed a significant positive relationship ( $p < 0.05$ ) between the extension support and the probability of application use. The odds ratio value of the extension support presents that a one-unit increase tends to increase the opportunity of mobile application use by 5.00 times, assuming the other independent variables remain constant. Extension support plays a crucial role in influencing these factors by providing farmers with access to practical information, advisory services, and resources through interactive voice responses, short messaging services, real-time data on weather, market prices, and disease alerts (Sennuga *et al.*, 2023). Factors such as perceived usefulness, social influence, and information awareness significantly influence farmers' adoption of mobile applications, whereas perceived risk and cost act as barriers to adoption (Okoroji *et al.*, 2021). Therefore, effective extension support is essential for promoting the adoption and successful use of mobile applications in livestock farming, bridging the gap between technology and farmers' needs.

We found a significant positive relationship ( $p < 0.05$ ) between membership association and the probability of application use. The odds ratio value shows that if membership association increases by one unit, then the ratio of the possibility of mobile application use increases by 4.30 times, assuming the other independent variables remain. The role of association members is crucial as they influence

farmers' decisions through peer interactions and shared experiences, impacting smartphone use patterns within the community (Ma *et al.*, 2023). Existing literature suggests that farm advisors, family, and peers are important support networks that assist farmers in using smartphone applications effectively (Michels *et al.*, 2019). Associations can leverage these social connections to encourage members to adopt and utilize mobile applications for various livestock management tasks, such as data recording, herd health monitoring, and informed decision-making. Therefore, promoting collaboration and knowledge sharing among association members enhances the adoption and effective utilization of mobile applications in livestock farming, improving productivity and decision-making processes. Furthermore, associations play a crucial role in ensuring that mobile applications developed for livestock farming are truly relevant, useful, and easy to use for their members (Schulz *et al.*, 2022). By actively engaging with application developers and providing feedback on the needs and preferences of their members, associations can shape the design and functionality of these applications, increasing their adoption and use (Kenny & Regan, 2021).

This study highlights the key factors affecting smallholder farmers' adoption of digital tools, providing important insights for policy development in Thailand and similar tropical regions. Education, training programs, extension services, and farmer associations are important factors that influence adoption. Policies should prioritize digital literacy initiatives, practical training, and the incorporation of user-centered applications designed for local farming contexts. Enhanced extension services and strong farmer associations can promote knowledge dissemination and collaboration. Improving rural Internet infrastructure and supporting digital resources are essential for addressing barriers to affordability and availability.

## CONCLUSION

The most significant variables of mobile application adoption for livestock management among smallholder farmers in Northern Thailand included education, participation in training programs, extension support, and membership in farmer associations. These factors significantly increase mobile application use, highlighting the necessity of developing digital literacy and encouraging technology adoption through specific measures, including educational initiatives and integrated training programs. Empowering farmers with the knowledge and ability to use mobile technology efficiently will contribute to the fundamental goals of rural development and sustainable agricultural practices.

## CONFLICT OF INTEREST

There are no conflicts of interest with any personal, financial, or other organizations connected to the subject matter discussed in this manuscript.

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## REFERENCES

- Baba, S., Dagong, M. I. A., Sohrah, S., & Utamy, R. F. (2019). Factors affecting the adoption of agricultural by-products as feed by beef cattle farmers in Maros regency of South Sulawesi, Indonesia. *Tropical Animal Science Journal*, 42(1), 76–80. <https://doi.org/10.5398/tasj.2019.42.1.76>
- Balehegn, M., Duncan, A., Tolera, A., Ayantunde, A. A., Issa, S., Karimou, M., Zampaligré, N., André, K., Gnanda, I., Varijakshapanicker, P., & Kebreab, E. (2020). Improving adoption of technologies and interventions for increasing supply of quality livestock feed in low- and middle-income countries. *Global Food Security*, 26, 100372. <https://doi.org/10.1016/j.gfs.2020.100372>
- Barrios, D., Olivera-Angel, M., & Palacio, L. G. (2023). Factors associated with the adoption of mobile applications (Apps) for the management of dairy herds. *Revista de Economía e Sociología Rural*, 61(4), 264382. <https://doi.org/10.1590/1806-9479.2022.264382>
- Baseca, C. C., Sendra, S., Lloret, J., & Tomas, J. (2019). A smart decision system for digital farming. *Agronomy* 9(5), 216. <https://doi.org/10.3390/agronomy9050216>
- Batla, A. B., Kikani, Y. B., Joshi, D. G., & Patel, K. (2023). Real time cattle health monitoring using IoT, ThingSpeak, and a mobile application. *Journal of Ethology & Animal Science*, 5(1), 1–7. <https://doi.org/10.23880/jeasc-16000131>
- Chandrarathna, R. M. D. S. M., Weerasinghe, T. W. M. S. A., Madhuranga, N. S., Thennakoon, T. M. L. S., Gamage, A., & Lakmali, E. (2022). "The Taurus": Cattle breeds and diseases identification mobile application using machine learning. *International Journal of Engineering Management Research*, 12(6), 198–205. <https://doi.org/10.31033/ijemr.12.6.27>
- Dhraief, M. Z., Bedhiaf, S., Dhehibi, B., Oueslati-Zlaoui, M., Jebali, O., & Ben-Youssef, S. (2019). Factors affecting innovative technologies adoption by livestock holders in arid areas of Tunisia. *New Medit*, 18(4), 3–18. <https://doi.org/10.30682/nm1904a>
- Ifeoma, L. S. W., Adelabu, A. W., & Olayemi, S. S. (2021). Technology adoption capabilities of small farm dairy cattle holders in Gwagwalada, Abuja: Effects of asymmetric information and extension approaches. *International Journal of Agricultural Economics*, 6(6), 320–328. <https://doi.org/10.11648/j.ijae.20210606.20>
- Junior, S. L. C., Balthazar, G. R., & Silva, I. J. O. (2021). Development and validation of a mobile app for the diagnosis of heat stress in livestock animals. *International Journal of Agricultural, Environmental and Bioresearch*, 6(3), 209–222. <https://doi.org/10.35410/IJAEB.2021.5639>
- Kambale, P. D. R., Patil, D., & Ganavi, N. R. (2024). Mobile technology for farmers: An overview of agricultural apps. *Asian Journal of Agricultural Extension, Economics & Sociology*, 42(9), 75–81. <https://doi.org/10.9734/ajaees/2024/v42i92543>
- Kenny, U., & Regan, A. (2021). Co-designing a smartphone app for and with farmers: Empathising with end-users' values

- and needs. *Journal of Rural Studies*, 82, 148–160. <https://doi.org/10.1016/j.jrurstud.2020.12.009>
- Louta, M., Panagiotis, K., Vasiliki, P., Sotiria, V., Evangelos, T., Stergios, P., Georgia, K., Alexandros, T., Socratis, D., & Georgios, A. (2023). FarmDain, A decision support system for dairy sheep and goat production. *Animals*, 13(9), 1495. <https://doi.org/10.3390/ani13091495>
- Ma, W., Owusu-Sekyere, E., Zheng, H., & Owusu, V. (2023). Factors influencing smartphone usage of rural farmers: Empirical analysis of five selected provinces in China. *Information Development*, 1-14. <https://doi.org/10.1177/02666669231201828>
- Mansour, T. (2022). Factors affecting mobile phone usage by farmers as a source of agricultural information in Sharqia governorate, Egypt. *Journal of Tekirdag Agriculture Faculty*, 19(2), 412–425. <https://doi.org/10.33462/jotaf.1013886>
- Michels, M., Bonke, V., & Musshoff, O. (2019). Understanding the adoption of smartphone apps in dairy herd management. *Journal of Dairy Science*, 102(10), 9422–9434. <https://doi.org/10.3168/jds.2019-16489>
- Mohanty, A. K., Rao, T. K., Harisha, K. S., Agme, R., Gogoi, C., & Velu, C. M. (2024). IoT applications for livestock management and health monitoring in modern farming. *Educational Administration: Theory and Practice*, 30(4), 2141–2153.
- Nasirahmadi, A., & Hensel, O. (2022). Toward the next generation of digitalization in agriculture based on digital twin paradigm. *Sensors*, 22(2), 498. <https://doi.org/10.3390/s22020498>
- Navulur, S., Sastry, A. S. C. S., & Prasad, M. N. G. (2017). Agricultural management through wireless sensors and Internet of Things. *International Journal of Electrical and Computer Engineering*, 7(6), 3492–3499. <https://doi.org/10.11591/ijece.v7i6.pp3492-3499>
- Okoroji, V., Lees, N. J., & Lucock, X. (2021). Factors affecting the adoption of mobile applications by farmers: An empirical investigation. *African Journal of Agricultural Research*, 17(1), 19–29. <https://doi.org/10.5897/AJAR2020.14909>
- Palacpac, E. P., Balingit, K. A. M. P., Bonifacio, A. A. D., Villanueva, M. A., Tolentino, R. B., Uy-DeGuia, M. R. D. L., Llantada, P. L. T., Castillo, C. I., Brul, B. J., Rubio, H. C. A., & Abes, M. M. (2024). Evaluating the usability, perceived performance, and perceived effects of KBGAN iHealth© and KBGAN iFeed© mobile apps for buffalo management in selected municipalities in the Philippines. *Journal of Buffalo Science*, 13, 31–45. <https://doi.org/10.6000/1927-520X.2024.13.04>
- Saengwong, S., Intawicha, P., & Phuwisaranakom, P. (2021). Assisting knowledge dissemination of postpartum beef cows management using smartphone-based technology. *Walailak Journal of Science and Technology*, 18(11), 10695. <https://doi.org/10.48048/wjst.2021.10695>
- Schulz, P., Prior, J., Kahn, L., & Hinch, G. (2022). Exploring the role of smartphone apps for livestock farmers: Data management, extension and informed decision making. *Journal of Agricultural Education and Extension*, 28(1), 93–114. <https://doi.org/10.1080/1389224X.2021.1910524>
- Sennuga, S. O., Ujoyi, S. A., Bamidele, J., Onjewu, S. S., Lai-Solarin, W. I., & Omole, A. A. (2023). Exploring the role of smartphone apps for livestock farmers' data management, extension, and informed decision making in Nigeria. *International Journal of Probiotics and Dietetics*, 3(2), 46–53. <https://doi.org/10.33140/IJPD.03.02.01>
- Shanka, D. S., & Genale, A. H. (2022). Mobile application-based expert system for cattle disease diagnosis and treatment in Afan Oromo language. *International Journal of Information Systems and Informatics*, 3(3), 131–149. <https://doi.org/10.47747/ijisi.v3i3.856>
- Szafraniec-Siluta, E., Zawadzka, D., & Strzelecka, A. (2022). Application of the logistic regression model to assess the likelihood of making tangible investments by agricultural enterprises. *Procedia Computer Science*, 207, 3894–3903. <https://doi.org/10.1016/j.procs.2022.09.451>
- Thar, S. P., Ramilan, T., Farquharson, R. J., Pang, A., & Chen, D. (2021). An empirical analysis of the use of agricultural mobile applications among smallholder farmers in Myanmar. *Electronic Journal of Information Systems in Developing Countries*, 87(2), e12159. <https://doi.org/10.1002/isd2.12159>
- The World Bank. (2020). Thailand rural income diagnostic: Challenges and opportunities for rural farmers. Retrieved May 5, 2024, from <https://documents.worldbank.org/en/publication/documents-reports>
- Triatmojo, A., Muzayyanah, M. A. U., Syahlani, S. P., & Guntoro, B. (2024). Demographic targeting of users in mobile applications for livestock digital marketing among smallholder cattle farmers. *Agrisoconomics: Jurnal Sosial Ekonomi Pertanian*, 8(2), 602–613. <https://doi.org/10.14710/agrisoconomics.v8i2.22722>
- Yuniarsih, E. T., Salam, M., Jamil, M. H., & Tenriawaru, A. N. (2024). Determinants determining the adoption of technological innovation of urban farming: Employing binary logistic regression model in examining Rogers' framework. *Journal of Open Innovation: Technology, Market, and Complexity*, 10(2), 100307. <https://doi.org/10.1016/j.joitmc.2024.100307>