Quest Journal of Management and Social Sciences
Volume 7 Issue 2: 426-445
ISSN Print: 2705-4527
ISSN Online: 2705-4535
Web: https://www.quest.edu.np

Adoption and Utilization of Information Technology in Agriculture: Evidence from Rupendehi, Nepal

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Received: 26 Sept 2025
Revised: 15 Oct 2025
Accepted: 17 Nov 2025
Published: 30 Dec 2025

How to cite this paper:
Khanal, R., Kandel, S., Chaudhary, R., Neupane, U., & Gyawali, A. (2025). Adoption and Utilization of Information Technology in Agriculture: Evidence from Rupendehi, Nepal. *Quest Journal of Management and Social Sciences, 7*(2), 426-445. https://doi.org/10.3126/qjmss.v7i2.87806

Abstract

Background: The use of information technology (IT) in agriculture is expanding globally however, its adoption among farmers in Nepal remains uneven. Several factors, including education, location, cost of equipment, and political support, may affect how farmers integrate IT tools into their farming practices. This situation is particularly relevant in mixed farming areas such as the Rupandehi district.

Purpose: The main objective of this study is to identify the major factors that influence farmers' adoption and use of IT in Rupandehi, Nepal. It also seeks to examine how variables such as educational background, financial condition, policy support, and geographic location affect IT adoption and to relate these outcomes to previous studies.

Design/methodology/approach: A quantitative research design was applied using a structured questionnaire distributed to 402 farmers. The collected data were analyzed using structural equation modeling (SEM) to test relationships between education, political support, equipment cost, and geographic location as predictors of IT adoption. The reliability and validity of the questionnaire were examined using Cronbach's alpha and factor analysis.

Findings: The findings from SEM revealed that political support had the strongest positive impact on IT adoption ($\beta = 0.497$, $p < 0.001$), followed by equipment cost, which had a moderate positive effect ($\beta = 0.175$, $p < 0.001$). Unexpectedly, higher levels of formal education were found to have a negative relationship with IT adoption ($\beta = -0.258$, $p < 0.001$), whereas geographic location had no significant effect. The model explained 73.8% of the total variance in IT adoption, confirming its reliability and validity.

Conclusion: The study concludes that consistent political and extension support, affordable equipment, and practical digital training are essential for promoting agricultural digitalization. The negative influence of higher education suggests a need for more targeted, context-based digital skill programs. Future qualitative research across multiple districts is encouraged to explore these findings further.

Keywords: Agriculture, Adoption, Information Technology, Rupandehi, Nepal

1. Introduction

Agriculture remains one of the primary sources of income in Nepal; however, many farmers still rely on traditional methods and do not fully benefit from modern information technology (IT). Many farmers still use traditional methods, even though modern digital tools can help them produce more food and earn a better income. Studies show that in Nepal, some farmers continue to rely on traditional farming practices. In contrast, others have started using digital tools such as mobile apps, weather updates, and market price alerts (Njuguna et al., 2025). However, access to these tools is unequal because factors such as education, cost, weak infrastructure, and location determine who can use them (Chaudhary et al., 2025). The government began providing weather-based farming information through mobile phones in 2015, and farmers in Rupandehi were among the first to receive these services (Mabhaudhi et al., 2025). Historically, Nepal introduced modern farming tools, such as ploughs and threshers, in 1964 with support from the Soviet Union. In recent years, mobile apps like IFA Krishi Nepal and Geo Krishi have gained popularity for providing crop and weather information (Pandey et al., 2025). These changes demonstrate that ICT can support agricultural modernization, although progress is uneven.

Information and Communication Technology (ICT) in farming encompasses mobile phones, machines, the internet, and advisory apps that aid farmers in improving productivity (Mollel et al., 2025). In Nepal, ICT encompasses tools such as hand tractors, SMS alerts for weather and market prices, and mobile apps for crop advice (Lamsal et al., 2023). ICT helps save time, improve decisions, and increase production. However, proper use of technology, known as e-agriculture, depends on whether farmers understand and trust the tools (Lin et al., 2017). Today, many farmers receive mobile messages about weather, crop care, and prices, which helps make farming smarter and more efficient (Sharma et al., 2021). However, despite the availability of mobile phones and internet access, many farmers in Nepal primarily use these technologies for entertainment rather than for farming (Wyche & Steinfield, 2016). As a result, crop yields remain low, incomes stay limited, and farmers often lack timely advice for decision-making (Shrestha & Khanal, 2020).

These challenges create a large gap between farmers who use technology and those who do not. Many small farmers also face barriers, including low levels of education, high equipment costs, poor roads, and political difficulties, that limit their ability to utilize ICT tools (Deichmann et al., 2016). Some districts, including Rupandehi, exhibit both traditional and modern farming practices coexisting side by side. Understanding why some farmers adopt ICT and others do not is crucial for designing effective policies and programs to support modern farming in Nepal. This study examines the key factors that influence the adoption of ICT in the Rupandehi district. It focuses on four main areas: farmers' education levels, the affordability of equipment, geographic location and access to networks, and the role of government support and political conditions. These factors together determine whether farmers adopt ICT and how it affects their production and income.

Previous studies in Nepal have many limitations. They used small sample sizes and focused on only a few districts, so the findings cannot be generalized to the entire country. Many studies have examined only basic tools, such as radios and phones, rather than modern tools like mobile apps, GPS devices, or online weather systems. Other studies employed weak methods, failed to examine interactions between key factors, and did not assess whether ICT actually improves crop yields or income. Many also overlooked essential issues, such as poor internet coverage, challenging geography, and political instability. This study addresses these gaps by utilizing a larger sample, a stronger methodology, and both quantitative and qualitative data to produce a more accurate and comprehensive understanding of ICT adoption.

This research is important because many farmers in districts like Rupandehi still lack equal access to modern agricultural technologies. Although tools like mobile phones, apps, and digital weather updates can help farmers earn more and reduce poverty, many farmers are left behind due to low education, poor infrastructure, high technology costs, and weak government support. Past studies have not examined these factors together in the context of Rupandehi. By examining why some farmers adopt ICT and others do not, this research will enable government agencies, NGOs, and agricultural institutions to develop more effective plans to support farmers. The goal is to enhance farming, alleviate poverty, and promote modern agricultural practices in Nepal.

2. Literature Review

Information technology (IT) is becoming very important in farming around the world (Mulungu et al., 2025). Farmers now utilize mobile phones, internet applications, weather alerts, and digital advice to cultivate more crops and enhance their income (Adla et al., 2025). However, many farmers, especially in developing countries like Nepal, still face big problems in adopting these technologies. This review summarizes the findings of past research on the primary factors that influence whether farmers adopt IT in agriculture. These factors include the farmers' education level, their location, the cost of equipment, and government support. This review also discusses the gaps in past research and explains what theories help us understand technology adoption.

Education and IT Adoption in Agriculture

Education is one of the most studied factors in technology adoption. Zachariou et al. (2025) found that farmers with higher levels of schooling or training use digital tools more successfully. For example, Mapiye et al. (2023) studied farmers in Nepal and India and found that farmers with better education are more likely to use mobile apps to receive weather updates and market prices. These farmers can read and understand technology more easily because they have more schooling.

Altieri (2004) explained that education helps people understand new ideas and trust new technology. Farmers who can read and write can use smartphones, watch farming videos, join online groups, and understand farming instructions. These skills enable them to make more informed farming decisions and enhance their crop production.

However, some studies find different results. Gittins et al. (2025) found in western Nepal that some young, educated farmers move to cities to find alternative employment, thereby discontinuing their farming practices and failing to adopt IT in agriculture. Schafer et al. (2025) demonstrated that when educated individuals leave farming to work in cities, the use of technology on family farms decreases because there is no educated person to manage it.

Past research has not fully explained why education sometimes increases IT use and sometimes does not. The gap is that most studies have only examined formal education (years in school) but have not investigated practical skills and experience. Additionally, researchers did not consider that educated farmers might leave farming altogether, which would reduce technology use in agriculture. This study will examine these gaps more carefully.

Geographic Location and Internet Connectivity

The residence of a farmer significantly impacts whether they can utilize digital tools (Abdulai et al., 2023). Farmers living near towns or cities usually have better mobile networks, electricity, and internet connections, which makes using smartphones and farming apps easier (Hammon & Goralnik, 2025). They also have easier access to training and support from agriculture offices.

In contrast, farmers in remote and mountainous areas often lack reliable internet signals or access to regular electricity (Elagib et al., 2025). Thapa et al. (2025) studied areas in Nepal and found that farmers living near highways or district centers use technology more frequently than those in remote villages. Yu et al. (2025) in China found that rural farmers in mountainous areas have much lower access to digital tools compared to farmers in lowland areas.

Karki et al. (2020) demonstrated that in Nepal, subsistence farmers in remote areas utilize less technology due to a lack of necessary infrastructure. However, Bhattarai and Conway (2021) noted that new mobile broadband and electricity projects are improving access in some rural areas, which may reduce location-based differences over time.

Previous studies have demonstrated that location affects technology use, but they have not investigated the construction of roads, electricity, and mobile network projects. Most studies were conducted several years ago, so we do not know if infrastructure improvements have reduced the location gap in recent times. This study examines whether location still matters as much in areas like Rupandehi that have improved infrastructure.

Cost of Equipment and Financial Barriers

The cost of digital equipment is often the biggest barrier for small farmers (Phasinam et al., 2024). Smartphones, intelligent farming machines, internet data plans, and sensors can be more expensive than what poor farmers can afford (Manono, 2025). Research by Hamza et al. (2025) from Pakistan and China found that high costs strongly discourage farmers from buying digital tools.

Rao (2007) explained that in developing countries, the cost problem is even more serious because farmer incomes are very low. Many farming households in Nepal have low incomes and are unable to afford smartphones or pay for data services. Some government programs offer subsidies or loans to help farmers, but studies examining whether these programs are effective are limited.

Supetran et al. (2021) suggested that sharing equipment within farmer groups or buying second-hand devices might be solutions to the cost problem. However, there is very little research data on how well these solutions actually work in Nepal's farming communities.

Past research has shown that cost is a barrier; however, researchers have not fully studied which costs matter most (e.g., buying equipment, paying for internet, training costs, etc.). Most studies were general and did not look at the specific context of Nepal. Additionally, few studies have examined whether government subsidies and support programs actually make technology affordable for low-income farmers. This research closely examines the specific cost issues in Rupandehi.

Government Support and Political Situation

The political environment and government policies significantly influence whether farmers utilize IT (Barbier, 2025). A stable and supportive government develops effective programs and policies to help farmers use digital tools (Petraki et al., 2025). These programs include providing training, offering subsidies, providing free apps, and improving mobile network coverage in villages.

In Nepal, the government initiated the e-agriculture program in 2015, which provides weather alerts and agricultural advice via mobile phones. Sigdel et al. (2022) found that districts like Rupandehi, which received this government support, showed higher rates of technology use among farmers. Sharma et al. (2021) studied mobile phone-based messaging and found that government programs encouraging farmers to use these messages increased the adoption of technology.

However, political problems, delays in funding, or poor program management can stop progress (Dzakaklo et al., 2024). Rose et al. (2016) explained that stable, clear, and transparent policies encourage farmers to trust and utilize IT tools more effectively. Partnerships with private companies and organizations also contribute to this effort, as demonstrated by Joshi and Rawat (2024), who studied Nepal and found that combined government and private support is more effective than government support alone.

Maharjan and Gonzalvo (2025) demonstrated that in Bagmati Province, Nepal, government policies and ongoing support enable farmers to adopt and utilize conservation farming practices. This shows that supportive policies increase adoption rates.

Past studies have shown that government support matters, but they have not fully explained how political stability affects all farmers equally or whether some farmers benefit more than others. Most studies did not compare what happens when government support is strong versus weak. Also, researchers did not examine how local politics (at the district and village level) affect farmer behavior. This research explores these gaps.

Theoretical Frameworks Explaining IT Adoption

The Technology Acceptance Model helps explain why farmers decide to use or not use new technology (Lin et al., 2017). This model suggests that farmers are more likely to adopt technology if they believe two key things: first, that the technology is useful and will enhance their farming practices; and second, that the technology is easy to use and understand. If farmers believe that IT tools help improve crops and make their work easier, they are more likely to adopt them.

Diffusion of Innovations theory explains how new ideas and technologies spread in a community over time (Mollel et al., 2025). This theory identifies different groups of adopters - some farmers are "innovators" who try new things first, some are "early adopters" who quickly accept new ideas, some are "late majority" who adopt after most people, and some are "laggards" who adopt last or never. The theory also explains that communication channels and social influence affect the rate at which new technology spreads.

These frameworks help explain how education, cost, location, and government support influence the adoption of technology. For example, well-educated farmers may perceive more usefulness in IT tools. Farmers living near towns with good infrastructure may find IT tools more accessible and easier to use. When the government provides training and support, farmers may have more trust and confidence in using technology.

Research Gaps

Most past studies examined only one or two factors affecting IT adoption. For example, some studied only education, while others studied only cost. Few studies looked at how education, cost, location, AND government support work together. This is important because these factors may interact and influence each other to determine whether farmers adopt technology. Many studies have used small numbers of farmers and focused on only a few villages or districts. This means the results cannot be trusted to represent all of Nepal or even all of one district. For example, a study might only interview 50 farmers from two villages, so we cannot say these findings apply to 10,000 farmers in the entire district.

Most past studies have focused only on basic tools, such as mobile phones and radios. They did not study modern technologies, such as mobile apps for farming, GPS machines, online weather systems, or digital advice services. Since technology is changing rapidly, studies on basic phones may not help us understand the adoption of modern digital tools. Most studies have examined farmers only once, a type of study known as a cross-sectional study. They did not follow the same farmers over months or years to see if they started using technology, stopped using it, or changed their approach to using it. This makes it hard to understand the real process of adoption.

Many studies have asked farmers if they use technology, but they have not checked whether using technology actually increases crop production or farmer income. We need to know if technology really helps farmers, not just whether they use it. Many studies did not discuss the real problems that prevent farmers from using technology, such as poor internet connections, difficult geography, local political issues, or a lack of trust in the government. These local problems are of great importance in Nepal but are often overlooked in research.

This study employs a robust research design with 402 farmers. We employ a statistical method called Structural Equation Modeling (SEM), which can examine how multiple factors interact to influence technology adoption. This research examines all four main factors together - education, cost of equipment, geographical location, and government support - to understand how they combine to affect farmers' IT adoption. This study examines the modern digital technologies that farmers actually use today, including farming apps, mobile alerts, GPS systems, and online advice services, rather than relying solely on basic phones from the past. We collected data on whether farmers actually produce more or earn more money when they use technology, rather than just whether they use technology or not. This study focuses specifically on the Rupandehi district, examining the local geography, government support, costs, and education levels that impact farmers in this area.

Policy Review

Nepal has established several national policies promoting the use of technology in agriculture, including the ICT Policy (2015), the Agriculture Mechanization Policy (2014), and the Right to Food Act (2018). The effectiveness of these policies at the grassroots level remains uneven. For example, the Fifteenth Plan's emphasis on digital platforms aligns with the increased mobile phone use observed in Rupandehi; however, persistent issues such as poor rural internet access and a lack of digital literacy, noted in this study, suggest gaps between policy intentions and local realities.

At the local governance level, towns such as Butwal and Tilottama have incorporated digital applications and engagement approaches towards citizens; this has helped them to be more responsive to the services. Despite these developments, the study's results indicate the following problems: a low level of awareness among farmers about existing digital resources and an insufficient representation of marginalized groups. This means that local policy execution is not always aligned with national targets. Such a gap necessitates better coordination and capacity-building to ensure that policies are effectively translated into wider technology adoption.

Moreover, the favorable impact of political support on the usage of IT that the research revealed makes it clear that it is possible to enhance political commitment and further adapt policy frameworks to the needs of rural farmers. This study highlights key aspects of intervention, including digital literacy training, infrastructure development, and inclusive program design, that can be implemented to enhance the effectiveness of current policy and accelerate digital agricultural transformation in Nepal by critically connecting policy provisions with empirical study findings on the matter.

Hypothesis

Farmers with higher levels of education are generally better equipped to understand and utilize new tools and technologies (Vecchio et al., 2020). They are more likely to know how to use smartphones, apps, the internet, and other digital tools that help with farming. Educated farmers can read market information, watch farming videos, use weather apps, and join online farming groups (Mapiye et al., 2023). These skills enable them to make better decisions and enhance their crop yields. On the other hand, farmers with little or no education may find it challenging to utilize such technology and may rely more heavily on traditional farming methods (Altieri, 2004). In rural areas like Rupandehi, this disparity is clearly evident. Therefore, education plays a significant role in whether a farmer uses digital technology. This hypothesis suggests that better education increases the chance of using IT in farming.

H_1: Farmers with a higher level of education are more likely to use information technology (IT) in agriculture.

Where a farmer lives can significantly impact their ability to utilize digital tools for farming (Abdulai et al., 2023). Farmers in towns or closer to markets typically have better access to mobile networks, electricity, internet, and training opportunities (Hammon & Goralnik, 2025). These facilities make it easier for them to use smartphones, check online weather forecasts, or get price updates. In contrast, farmers in remote or hilly areas may not have a stable internet connection or regular electricity. They may also have fewer training opportunities and less support from agriculture offices. In places like Rupandehi, farmers living near the highway or district centers may use more technology than those in remote villages. This indicates that geographical location has a significant impact on the adoption of IT in agriculture. This hypothesis aims to understand how a farmer's location affects the likelihood of using digital technology in farming.

H_2: Farmers living in better-connected and developed areas are more likely to use information technology in agriculture.

Many useful farming tools, such as GPS tractors, mobile apps, weather devices, and irrigation sensors, are expensive (Phasinam et al., 2024). Poor or small-scale farmers often cannot afford these tools, even if they are aware of their benefits (Manono, 2025). In rural Nepal, many farmers have low incomes and are unable to afford smartphones or pay for data plans. Even basic digital farming tools may be too costly for them. On the other hand, farmers who can afford these tools are more likely to use them for better planning, farming, and marketing (Nguyen & Hoang, 2025). The cost becomes a significant barrier, especially when there is no government support or subsidy. This hypothesis suggests that fewer farmers use digital tools when the equipment is too expensive. Understanding this link will help policymakers create affordable technology or support programs for small farmers.

H_3: The High cost of digital equipment reduces the use of information technology in agriculture.

The political environment is crucial in the development of agriculture (Barbier, 2025). When the government is stable and supportive, it develops effective programs and policies to help farmers utilize digital tools (Petraki et al., 2025). These include training, subsidies, free apps, or building better village mobile networks. In contrast, if there is political instability or poor planning, farmers may not receive the necessary assistance. Corruption, delays in policy implementation, or weak governance can hinder the progress of digital farming. In areas like Rupandehi, where the government has introduced digital farming programs (e.g., "Smart Village"), farmers are more encouraged to use IT tools (Ministry of Agriculture, 2021). However, such programs work best with clear leadership, proper funding, and political support (Maharjan & Gonzalvo, 2025) labor shortages, and the increasing feminization of farming due to male outmigration. Environmental Conservation Agriculture (ECA. This hypothesis examines how political stability and effective policies facilitate the adoption of digital technology by farmers in their daily farming activities.

H_4: A stable political situation and supportive policies encourage the use of information technology in agriculture.

3. Methods

Research Design and Methodology

This study employed a quantitative research design to investigate the key factors influencing the adoption and utilization of information technology (IT) among farmers in Rupandehi District, Nepal. A survey method was selected to collect standardized data that would enable statistical analysis of the relationships between several variables, including education, costs, political support, and location. The district Rupandehi was chosen because it reflects the representative features of mixed farming activities and digital programs. The sample size of 402 farmers was selected based on population estimates and statistical power requirements to provide confidence and make the findings relevant to the district's context.

The main instrument of analysis was chosen as Structural Equation Modelling (SEM) because it can compare the relationships between several latent variables in one study, and it will help in achieving a comprehensive picture of the interplay between educational level, equipment cost, geographical location, and political factors in influencing IT adoption. Although alternative techniques, including multiple regression, can address predictive relationships, they cannot account for the complex effects of relationships and measurement errors; consequently, SEM is more relevant to the objectives of this study. It will utilize validated survey tools, reliability pre-testing, and address ethical concerns to enhance the rigor and credibility of the research results.

Population, Sampling, and Data Collection

The target population consisted of all active farmers in Rupandehi District involved in crop production. A multistage sampling approach was employed to ensure the sample's representativeness. First, villages with significant agricultural activities were purposively selected. Within those villages, farmers were randomly chosen to participate. The final sample size consisted of 402 farmers, determined based on population estimates and the need for statistically meaningful analysis. Only farmers who were actively engaged in crop farming were included in the survey.

Data was gathered using a structured questionnaire developed from the review of existing literature and validated research tools. The questionnaire was first written in English and then translated into Nepali for clarity of the responses. It included sections on: demographic information, access and exposure to digital technologies, education and economic background, and perceptions of government and market support.

Respondents were asked to rate their agreement with statements related to each variable using a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). The instrument was tested for clarity in a pilot phase before the main survey. Informed consent was obtained from all participants.

Measurement of Variables

IT Use in Agriculture: Assessed using six items adapted from Paudel et al (2018), Shrestha et al. (2020), Khatri et al. (2024), and World Bank (2019), focusing on indicators such as regular use of mobile apps, seeking information about market prices online, and using digital devices for farming tasks. An example item is: "I regularly use mobile apps for weather forecasts and crop planning".

Education Level: Measured with a five-item scale from Thapa and Shrestha (2019) and Singh and Aryal (2023) which evaluates how the respondent's education helps in understanding and using IT tools. An example item is: "Education increases confidence in using IT tools".

Equipment Cost: Evaluated using six items adapted from Rao (2007) and Arangurí et al. (2025), capturing whether high cost and affordability hinder technology use. An example item is: "I would use more IT if the equipment cost were lower".

Political Situation: Assessed using six items from Joshi and Rawat (2024)climate change, government investments, land and property rights and gender. The primary source of data is used to assess the opinions of respondents regarding technology adoption, (Begho, 2022; Ministry of Agriculture, 2021), capturing whether government policies and local support make IT adoption easier. An example item is: "Government provides training or subsidies for IT in farming".

Geographical Location: Measured with a seven-item scale adapted from Karki et al. (2020) and Mishra et al. (2024), looking at how location and infrastructure influence access. An example item is: "Internet and mobile coverage in my area supports digital farming". All items were rated on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree), with higher scores showing more positive results for each variable.

4. Results

After data collection, responses were checked, coded, and entered into statistical software for analysis. The relationships and effects between variables were then tested using Structural Equation Modeling (SEM), which allows simultaneous analysis of multiple predictors and their direct and indirect impacts on IT adoption. The reliability and validity of the measurement scales were assessed using Cronbach's alpha, factor loadings, composite reliability, and average variance extracted (AVE). The model fit was evaluated using indices such as the Standardized Root Mean Square Residual (SRMR) and the Normed Fit Index (NFI).

Ethical Considerations

All data collection procedures adhered to national and institutional ethical guidelines for research with human participants. Farmers were briefed on the study's aims, and their consent was sought and documented. Confidentiality was strictly maintained; individual identities were not disclosed at any stage. Participation was entirely voluntary, and respondents could withdraw at any point without consequence. Cultural sensitivities and local norms were respected throughout fieldwork.

Table 1: Demographic Characteristics

Respondent Info	Categories	Frequency (n)	Percentage (percent)
Age Distribution	Below 25 years	46	11.4
	25–35 years	112	27.9
	36–45 years	104	25.9
	46–55 years	82	20.4
	Above 55 years	58	14.4
Gender	Male	258	64.2
	Female	144	35.8
Education Level	No formal education	76	18.9
	Primary (1–5 class)	92	22.9
	Secondary (6–10 class)	104	25.9
	Higher secondary (10+2)	82	20.4
	Bachelor's and above	48	11.9
Farm Size	< 1 hectare (smallholding)	168	41.8
	1–2 hectares	126	31.3
	2–5 hectares	76	18.9
	> 5 hectares	32	8
Type of Farming	Crop production	158	39.3
	Horticulture	84	20.9
	Livestock	108	26.9
	Fish farming	52	12.9
Location	Rural villages	246	61.2
	Peri-urban areas	156	38.8
Access to Technology	Basic phone	226	56.2
	Smartphone	134	33.3
	Digital farming tools	42	10.4
Income Sources	Only farming	238	59.2
	Farming + small business	92	22.9
	Farming + remittances	72	17.9

Table 1 illustrates the 402 farmers surveyed. Their ages varied. Most farmers, approximately 28, were between 25 and 35 years old. The largest groups were those aged 36 to 45, at 26 percent, and 46 to 55, at 20 percent. Fewer farmers were below 25 or over 55 years old. More than half of the respondents, 64%, were male, and about 36% were female. Education levels were different among the farmers. About 19 percent had no formal education. Around 23 percent completed primary school, and 26 percent finished secondary school. Some 20 percent had higher secondary education, and nearly 12 percent had a bachelor's degree or higher.

Farm sizes also varied. Most farmers, i.e., 42 % had small farms of less than 1 hectare. Approximately 31% had farms between 1 and 2 hectares. Nearly 19 percent had farms between 2 and 5 hectares, and 8 percent had farms larger than 5 hectares. Regarding the type of farming, 39 percent focused on crop production. Others raised livestock 27 percent, practised horticulture 21 percent, or engaged in fish farming 13 percent. Most farmers lived in rural villages (61 percent), while the rest lived in peri-urban areas (39 percent). Regarding technology access, over half, i.e., 56 % owned basic phones. About one-third had smartphones. Only a few farmers, 10 percent, used digital farming tools. Finally, most farmers, 59%, earned their income only from farming. Some combined farming with small businesses, at 23%, and relied on remittances, at 18%.

Table 2: Factor Loading of Indicators, VIF, and Reliability

Constructs	No	Items	CA	VIF	FL	CR	AVE
Cost of Equipment (CE)	6	CE1	0.955	4.113	0.908	0.956	0.816
		CE2		3.957	0.905		
		CE3		3.451	0.888		
		CE4		3.714	0.898		
		CE5		4.018	0.905		
		CE6		4.483	0.918		
Education Level (EL)	5	EA1	0.936	3.270	0.893	0.937	0.797
		EA2		3.187	0.891		
		EA3		3.273	0.896		
		EA4		3.013	0.882		
		EA5		3.525	0.903		
Geographical Location (GL)	7	GL1	0.931	2.843	0.853	0.937	0.708
		GL2		2.903	0.858		
		GL3		2.963	0.848		
		GL4		2.989	0.855		
		GL5		3.055	0.861		
		GL6		3.172	0.868		
		GL7		1.576	0.737		
IT in Agriculture Use (IA)	6	IA1	0.947	3.450	0.890	0.947	0.791
		IA2		3.116	0.875		
		IA3		3.602	0.891		
		IA4		3.576	0.892		
		IA5		3.390	0.888		
		IA6		3.719	0.899		
Political Situation (PS)	6	PS1	0.941	3.034	0.874	0.941	0.773
		PS2		3.173	0.880		
		PS3		3.448	0.891		
		PS4		3.328	0.888		
		PS5		2.817	0.861		
		PS6		3.148	0.879		

The measurement model was evaluated using five constructs: Cost of Equipment (CE), Education Level (EL), Geographical Location (GL), IT in Agriculture Use (IA), and Political Situation (PS). Each construct was measured with multiple items ranging from five to seven. The internal reliability of the constructs was examined using Cronbach's Alpha (CA) and Composite Reliability (CR). All constructs showed high reliability, with CA values between 0.931 and 0.955 and CR values between 0.937 and 0.956, exceeding the recommended cut-off value of 0.70 (Hair et al., 2019) yet concise, overview of the considerations and metrics required for partial least squares structural equation modeling (PLS-SEM. This indicates that the items used to measure each construct demonstrated strong internal consistency.

Convergent validity was assessed using factor loadings (FL) and Average Variance Extracted (AVE). Most factor loadings exceeded 0.85, showing that the items were strongly related to their respective constructs. Only one item (GL7 = 0.737) loaded slightly lower but remained above the acceptable threshold of 0.70. The AVE values for all constructs ranged from 0.708 to 0.816, which are well above the minimum recommended value of 0.50 (Fornell & Larcker, 1981), confirming adequate convergent validity. Additionally, multicollinearity was assessed using the Variance Inflation Factor (VIF), and all values were below the threshold of 5.0 (Hair et al., 2019), indicating that multicollinearity was not a concern in this model.

In summary, the results confirmed that the constructs used in this study were both valid and reliable. The high CA, CR, and AVE values demonstrate strong internal consistency and convergent validity, ensuring the measurement model is appropriate for further structural model analysis.

Table 3: Fornell Larcker

	CE	EL	GA	IA	PS
CE	0.904				
EL	-0.658	0.893			
GA	0.765	-0.502	0.841		
IA	0.783	-0.700	0.659	0.889	
PS	0.858	-0.642	0.764	0.825	0.879

Table 3 shows the Fornell–Larcker criterion, which is used to check discriminant validity. The numbers in the diagonal (bold values) are each construct's square roots of the Average Variance Extracted (AVE). These values are CE (0.904), EL (0.893), GA (0.841), IA (0.889), and PS (0.879). For discriminant validity to hold, each diagonal value should be higher than the correlations with other constructs in the same row or column. In this table, all diagonal values are greater than the off-diagonal values. This means that each construct is more strongly related to its own items than to those of other constructs (Astrachan et al., 2014). Therefore, the discriminant validity of the model is confirmed.

Table 4: HTMT Ratio

	CE	EL	GA	IA	PS
CE					
EL	0.695				
GA	0.787	0.52			
IA	0.822	0.743	0.682		
PS	0.905	0.684	0.799	0.873	

Table 4 presents the Heterotrait–Monotrait (HTMT) ratio of correlations. This method also checks discriminant validity. According to standard guidelines, HTMT values should be below 0.90 to 0.95 (Henseler et al., 2015). The HTMT ratios range from 0.52 to 0.905. Most values are below 0.90, showing acceptable discriminant validity. Only one value, between CE and PS, equals 0.905, which is slightly higher than the threshold, but the difference is negligible. This suggests that the constructs are distinct and that discriminant validity is generally supported.

Table 5: Model Fit

	Saturated model	Estimated model
SRMR	0.064	0.064
Chi-square	990.491	990.491
NFI	0.918	0.918

The overall model fit was assessed using several fit indices, including the Standardized Root Mean Square Residual (SRMR), the Chi-square statistic, and the Normed Fit Index (NFI). The SRMR value was 0.064 for both the saturated and estimated models, below the recommended threshold of 0.08, indicating a good model fit (Hu & Bentler, 1999). The Chi-square value was 990.491 in both models. Although the Chi-square test is widely reported, it is often sensitive to sample size and may overestimate poor fit in larger samples (Fan et al., 2016). Therefore, complementary indices are also considered. The NFI value was 0.918 for both models, which exceeds the recommended cutoff value of 0.90, suggesting that the hypothesized model fits the data adequately. Together, these results demonstrate that the model shows an acceptable and reliable fit, supporting its use for further structural analysis.

Table 6: Coefficient of Determination (R^2)

	Original sample (O)
IA	0.738

Table 6 presents the coefficient of determination (R^2) for IT in Agriculture Use (IA). The R^2 value for IA is 0.738, indicating that the independent variables in the model explain 73.8% of the variance in IT adoption in agriculture. According to Chin (1998), an R^2 value above 0.67 is considered substantial, suggesting that the model has strong explanatory power. This means that most of the changes in IT use among farmers can be predicted by the selected factors, and the model is reliable for understanding the determinants of IT adoption in agriculture.

Table 7**:** Effect Size (f^2)

	CE -> IA	EL -> IA	GA -> IA	PS -> IA
Original sample (O)	0.025	0.138	0	0.213

Table 7 shows that the effect of the cost of equipment on IA was minimal ($f^2 = 0.025$), indicating that financial barriers play only a limited role in explaining technology use. The education level showed a medium effect ($f^2 = 0.138$), suggesting that farmers' educational background has a significant impact on the adoption of IT. Geographical location did not contribute to IT use ($f^2 = 0.000$), implying that differences in location did not significantly affect farmers' technology adoption. The political situation demonstrated the most significant effect ($f^2 = 0.213$), highlighting that supportive or unstable political conditions have a substantial influence on the use of IT in agriculture. According to F. Hair Jr. et al. (f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively. Based on this guideline, the findings indicate that the political situation and education are the most influential determinants, while cost plays a minor role, and location has no effect. These results reinforce the importance of non-financial factors, particularly governance and human capital, in shaping the adoption of agricultural technology (Hair et al., 2019).

Table 8**:** Hypothesis

	β	S.D	T-value	P values	2.50 percent	97.50 percent	Decision
CE -> IA	0.175	0.051	3.422	0.001	0.077	0.277	Accept
EL -> IA	-0.258	0.039	6.653	0.001	-0.333	-0.181	Accept
GA -> IA	0.015	0.039	0.387	0.699	-0.062	0.091	Reject
PS -> IA	0.497	0.057	8.687	0.001	0.402	0.606	Accept

Table 8 presents the results of hypothesis testing for the structural model. The path coefficient from equipment cost to IT in agriculture (CE → IA) was positive and significant (β = 0.175, t = 3.422, p = 0.001). The equipment costs moderately influence the adoption of IT, suggesting that affordability plays a role in farmers' willingness to adopt technology. In contrast, the relationship between education level and IT in agriculture (EL → IA) was negative and significant (β = –0.258, t = 6.653, p = 0.001). This unexpected finding suggests that higher education among farmers may not necessarily encourage IT adoption, possibly due to alternative employment opportunities or a shift away from traditional farming practices. Geographical location showed no significant effect on IT adoption (GA → IA; β = 0.015, t = 0.387, p = 0.699), indicating that regional differences in farming areas did not strongly predict technology use in this study.

Finally, the political situation exhibited the most potent positive effect on IT in agriculture (PS → IA; β = 0.497, t = 8.687, p = 0.001). This highlights that stable and supportive political conditions are critical for promoting the use of IT in farming.

Overall, making equipment more affordable and strengthening political support are key to increasing technology adoption among farmers. Understanding the different roles of education and location can help create better support programs for all types of farmers. These steps can improve farming success and rural livelihoods.

Figure 1**:** Path Analysis

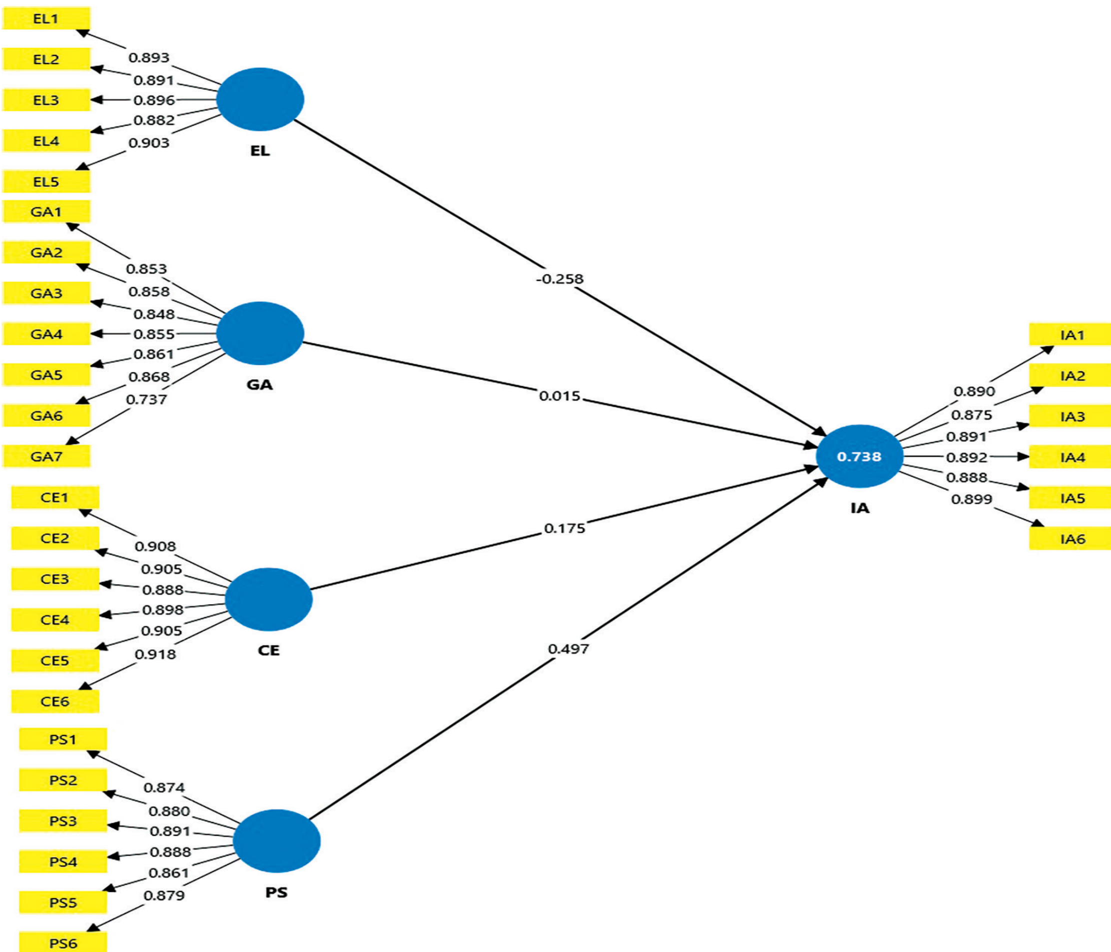

Table 9**:** Quadratic Test

Indicator	P values	Decision
QE (CE) -> IA	0.34	Insignificant
QE (EL) -> IA	0.309	Insignificant
QE (GA) -> IA	0.414	Insignificant
QE (PS) -> IA	0.582	Insignificant

Table 9 presents quadratic test results, which examine whether curvilinear (non-linear) relationships exist between the independent variables and IA. The findings show that the p-values for QE (CE) → IA ($p = 0.34$), QE (EL) → IA ($p = 0.309$), QE (GA) → IA ($p = 0.414$), and QE (PS) → IA ($p = 0.582$) are all above the conventional significance threshold of 0.05. This indicates that none of the quadratic effects are statistically significant; therefore, the relationships between the independent variables and IA remain linear rather than curvilinear. These results suggest that adding quadratic terms does not improve the model's explanatory power (Hair et al., 2021).

5. Discussion

This study provides important insights into the factors influencing the adoption of information technology in agriculture within Rupandehi, Nepal. However, some findings, such as the negative or weak relationship between education and IT adoption, are surprising and warrant further investigation. One possible reason is that higher-educated individuals move from farming to urban jobs, reducing their engagement with agricultural technology. This phenomenon has been observed in other rural areas of Nepal and South Asia, but warrants further research to understand the local socio-economic dynamics fully.

This study found that education level negatively correlated with IT use in agriculture. This result differs from what many past studies have found. Kalita et al. (2024) found that farmers with higher levels of education in India were more likely to use ICT tools. Similarly, Dhungana (2024) found that younger and more educated farmers in Dhankuta, Nepal, were more likely to utilize ICT in farming. However, the negative result in Rupandehi might happen because farmers with higher education often leave farming to find other jobs in cities. They may also think that traditional agriculture is not sufficient for their education. This aligns with Bohara and Gurung's (2025) findings in western Nepal, where educated farmers sometimes transitioned away from farming.

The political situation showed the most potent positive effect on IT adoption in this study. This finding matches many other studies. The government of Nepal began providing weather advice to farmers in 2015, and districts like Rupandehi were among the first to receive this assistance. Sigdel et al. (2022) also found that government policies and support programs helped farmers use more ICT tools in agriculture. Shrestha and Khanal (2020b) explained that stable politics and good government programs make farmers trust digital tools more. Farmers feel confident about trying new technology when the government provides training, subsidies, and sound policies.

The study found that high equipment costs reduce IT use, a finding that aligns with research from other countries. Chandio et al. (2024) studied wheat farmers in Pakistan and found that farmers who could not afford internet and digital tools had lower productivity. In China, Fan and Gan (2025) found that a 10% increase in equipment prices resulted in an 8% decrease in farmers' willingness to use digital tools. In rural Nepal, many farmers have low income and cannot buy smartphones or pay for data plans, as Alvi et al. (2025) also found. However, some farmers in Rupandehi who got subsidies from government programs were more likely to use IT tools.

This study found that geographical location did not significantly affect IT use. This result is surprising because many other studies found different results. Thapa et al. (2025) found that farmers in remote areas of Nepal had less access to mobile networks and electricity. Bhattarai and Conway (2021) also found that farmers living close to highways and markets used more technology than those in remote villages. However, the non-significant result in Rupandehi might be due to the district having better infrastructure than other parts of Nepal. Roads connect most villages in Rupandehi, and they have access to electricity, which helps reduce the difference between rural and urban areas.

Studies from other South Asian countries show similar patterns. Farmers who received ICT support through call centers in Bangladesh experienced improved crop production, particularly in remote areas. Munz et al. (2020) found that small farmers in Germany were increasingly using digital tools, but they required training and support. In India, Pal et al. (2022) found that IT helped farmers use fertilizers and water more efficiently and get better weather forecasts.

This research reveals both consistencies and differences compared with regional and international studies. For example, the strong positive influence of political support matches studies in Nepal and India, highlighting the pivotal role of government programs in digital adoption. On the other hand, the limited impact of geographical location diverges from earlier reports that emphasized connectivity issues in rural settings, suggesting that infrastructural improvements in Rupandehi might be reducing such barriers. These contrasts highlight the importance of contextualizing findings within specific local environments and avoiding generalizations across diverse regions.

Policy recommendations emerging from the study remain broad; therefore, there is a pressing need for more concrete and actionable strategies. For instance, targeted digital literacy training for farmers and local agricultural officers can bridge knowledge gaps. Furthermore, programs should prioritize inclusion of marginalized groups, including women and poor households, which are often excluded from technology benefits. Sustaining political support and ensuring coordination between national and local agencies will also be essential for effective technology dissemination. Future research should build on these findings, employing longitudinal methods to track changes over time and qualitative inquiries to gain a deeper understanding of farmers' experiences.

6. Conclusion

The results indicate that helping farmers utilize IT in agriculture requires action in several areas. Political support and government programs are crucial for promoting IT use. Making equipment cheaper through subsidies and training programs also helps. Education yields mixed results, suggesting that programs should prioritize practical skills over formal education alone. Although location did not matter much in Rupandehi, other areas with poor infrastructure still require better roads, electricity, and internet connections. Future research should investigate how these factors interact and include a broader range of districts to gain a deeper understanding of IT adoption in Nepal's agriculture. Nepal's ICT Policy (2015) and Agriculture Mechanization Policy (2014) aim to help farmers use technology. Local programs in municipalities like Tilottama utilize online systems to provide farmers with timely information. However, many rural areas still lack access to reliable internet and electricity. Digital programs like Smart Krishi and Geo Krishi are gaining popularity, but farmers primarily use smartphones for entertainment rather than for accessing farming advice.

Several studies identify common barriers to IT adoption in Nepal. Poor digital literacy, language problems, and network issues are significant challenges. Farmers often lack knowledge of information technology and face network issues. The Nepal Economic Forum (2025) reported that while 98 percent of people have access to mobile broadband, only 54 percent use the internet regularly. This indicates that having technology is insufficient; farmers also require training and support to utilize it effectively.

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