

Article

How Can Apple Farmers Be Encouraged to Apply Information Technology? The Moderating Effect of Knowledge Sharing

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Abstract: Information technology has become an increasingly powerful driving force in modern agriculture. In particular, its application is important for the sustainable development of the apple industry. However, to promote technology application effectively, a better understanding of the behavioral intention of apple farmers towards such information technology is needed. This study uses micro data from 226 Chinese apple growers and applies the theory of planned behavior. The factors influencing apple farmers' intention to choose information technology, along with factors influencing the transformation of that intention into actual behavior, are investigated through structural equation modeling. The results show that farmers' information technology attitudes and perceived behavioral control have a significant positive impact on their intention to choose information technology, and that intention has a significant positive impact on behavioral response. Additionally, both tacit and explicit knowledge sharing have a positive moderating effect on transforming the intention to choose information technology into actual behavior, and the higher the degree of knowledge sharing, the stronger its moderating effect. The results imply that to achieve industry sustainability, the government needs to improve its guidance and incentives for agricultural technology, as well as support the development of a strong knowledge-sharing system specifically for agricultural information technology.

Keywords: modern agriculture; apple industry; knowledge sharing; agricultural information technology; theory of planned behavior; structural equation model



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1. Introduction

Global agriculture has evolved through three stages: traditional agriculture, biochemical agriculture, and mechanized agriculture. The fourth and current stage is emerging now, namely, smart agriculture [1]. Agriculture 4.0 relies mainly on new technologies such as advanced agricultural information, the Internet of Things, and artificial intelligence [2]. In fact, China's 2021 Central Government's "No. 1 Document" also proposes the in-depth integration of a new generation of information technology with agricultural production and management [3]. How to promote the application of information technology in the agricultural field has become a key issue at home and abroad.

Apples are an important economic crop in China; in fact, China is the top producer and exporter of apples in the world, which has been critical for increasing farmers' incomes [4,5]. However, the aging labor force and rising production costs have severely restricted the sustainable development of the apple industry. An effective way to address these problems is to promote the application of information technology in the production of apples [3,5]. The information technology used in apple production mainly includes orchard environmental monitoring to observe the growth of apples, automatic water and fertilizer integration systems, pest monitoring and early warning technology, and apple grading and sorting machines.

As information technology can reduce labor and other costs, its implementation is conducive to sustainably modernizing the apple industry [5–7]. Therefore, from the

perspective of long-term sustainable development, it is necessary to analyze the factors affecting farmers' information technology choice intentions in apple production, and how to transform farmers' choice intentions into actual behaviors.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 discusses our model framework and establishes our hypotheses. Section 4 introduces our empirical methods and sample data. The empirical results are presented in Section 5. Section 6 provides a discussion, followed by the conclusions and policy implications in Section 7.

2. Literature Review

Information technology is a general term used to describe various technologies that assist in the management and processing of information, including sensor technology, intelligent technology, computer and communication technology, etc. [7,8]. At present, the combination of information technology and agricultural science is called agricultural information technology, which mainly studies the application of modern information technology in the field of agriculture [9–11].

As an important tool for realizing agricultural modernization, information technology has become a hot research topic in China and elsewhere in recent years. For example, Li [12] summarized the development of and latest achievements in agricultural information technology in China, while Zhao [13] added an international perspective, analyzing the development status of agricultural information technology in China and abroad, and explored potential research avenues in the field. Some scholars have conducted qualitative research on the characteristics and trends of the development of agricultural information technology. For example, Nie [14] summarized the characteristics of different information technologies used in agriculture before, during, and after production. Zhao [13] identified the trend that information technology is become more digital and precise. Other scholars have used mathematical models to quantitatively analyze agricultural information technology. For example, Cao [7] analyzed the factors affecting farmers' use of information technology in Beijing. Gu [6] analyzed the application of information technology in rural governance, using Zhejiang as a case. Zhang [8] measured the agricultural water poverty index based on information diffusion technology.

The application of information technology in agricultural production is also a hot research topic. This line of research focuses on the use of technology-generated information, e.g., for collecting and analyzing soil [15,16], using crop growth information to regulate crop production and forecast crop yields [17,18], and using spectral monitoring and remote sensing technology to monitor crop diseases and insects [19–22]. In addition, some scholars have evaluated the benefits of information technology in agricultural production. Aparjita [23] proposed that the use of information technology could help farmers obtain transparent price information and reduce production costs. Jensen [24] and Lee [25] suggested that the application of information technology could significantly increase the price of farmers' products and income [26,27]. Some scholars have also proposed that information technology can improve production efficiency and reduce labor costs [28–30].

However, the existing literature has some shortcomings. First, most scholars have focused on the application of information technology in field crops for domestic consumption, with little research on economic crops for international consumption [8,9,16,21]. Second, most studies have conducted research on information technology from a macro perspective, with few empirical studies at the micro level [12–14]. Third, the inconsistency between farmers' information technology choices and behaviors has largely been ignored.

Our study attempts to remedy these shortcomings. First, we examine the apple industry as a cash crop. We build a theoretical framework to analyze apple growers' information technology behavior, and investigate the factors influencing this behavior from three aspects: attitude, subjective norms, and perceived behavioral control. Specifically, we consider how choice behavior as well as internal and external factors influence this behavior. Second, through field research, we collect micro data on apple growers in Shandong

Province, China, paying attention to differences in behavior caused by farmer heterogeneity, to reveal the “black box” of the mechanism of information technology selection at the individual farmer level. Third, because farmers’ intention to choose information technology cannot completely explain their information technology behavior, we introduced the concept of knowledge sharing as a moderating variable, analyzing both tacit knowledge sharing and explicit knowledge sharing. We examine the role that knowledge sharing plays in transforming intention to choose technology into actual behavior. Our results have practical significance for improving farmers’ information technology choices, promoting the application of information technology in apple production, and ensuring the sustainable development of the industry.

3. Theoretical Framework and Research Hypotheses

3.1. Theory of Planned Behavior

The theory of planned behavior (TPB) was first proposed by Ajzen [31] to explain the mechanisms underlying human behavior and has long been the basis for research on many behaviors. The theory states that the factors that affect behavior fall under behavioral intention, and these indirectly affect behavioral performance. According to the theory, behavioral intention is affected by three related factors: “attitude”, “subjective norms”, and “perceived behavioral control” [32,33]. In this study, “attitude” refers to the positive or negative feelings of farmers towards information technology. “Subjective norms” refer to the external pressure farmers may feel when choosing information technology. “Perceived behavioral control” refers to the obstacles created by farmers’ personal experiences and expectations. Using TPB and applying it to farmer households, we designed a theoretical model for the study, as shown in Figure 1.

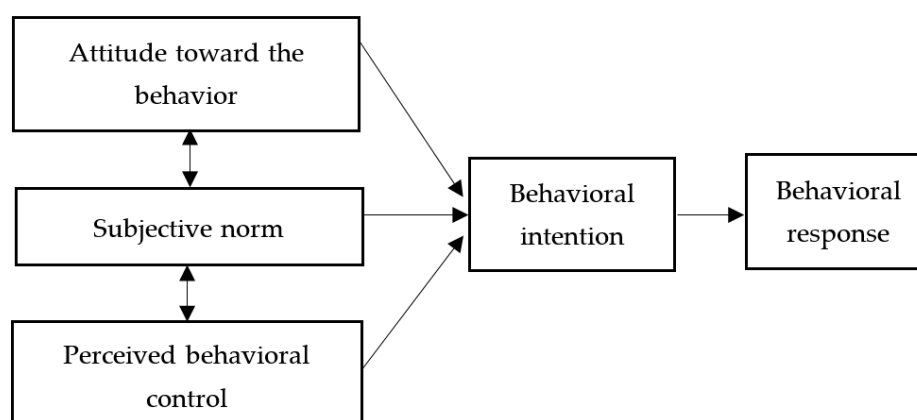


Figure 1. Theoretical framework of planned behavior.

3.2. Research Hypotheses

3.2.1. Attitude, Subjective Norms, Perceived Behavioral Control, and Information Technology Choice Intention

According to the research of Wu [32] and Li [34], behavioral attitudes are composed of two sub-dimensions: degree of inner orientation and degree of outer orientation. In this study, behavioral attitudes represent the farmers’ preference and income expectations for information technology choices [34,35]. Behavioral attitudes indirectly affect behavioral choice through willingness [33]. When farmers feel strongly about information technology and believe that technology will not only be conducive to apple production but will also bring other benefits, their positive attitudes improve their intention to choose technology [36].

Thus, Hypothesis 1 (H1) is proposed:

Hypothesis 1 (H1). *Farmers’ information technology behavior and attitudes have a positive effect on their intention to choose information technology.*

According to TPB [31], subjective norms refer mainly to external pressures that farmers experience from outside organizations or individuals when they choose information technology [33,37]. For farmers, these include county governments, village committees, agricultural material enterprises, and other farmers [36]. Some studies have shown that when these outside organizations or individuals have a positive attitude towards technology, it will promote farmers' willingness to choose technology [34,37].

Thus, Hypothesis 2 (H2) is proposed:

Hypothesis 2 (H2). *The subjective norms faced by farmers have a positive effect on their intention to choose information technology.*

Perceived behavioral control includes internal and external control [34]. Perceived behavioral control in this study refers to farmers' subjective understanding of their own ability and perceived external obstacles in the process of applying information technology [31,36]. When farmers think they already have the relevant knowledge and skills to apply information technology, they are more confident in choosing this technology [38]. Similarly, if farmers have more channels to readily obtain the resources they need to apply information technology, and cope with any difficulties encountered in production, their enthusiasm to choose information technology will increase [39].

Thus, Hypothesis 3 (H3) is proposed:

Hypothesis 3 (H3). *Farmers' perceived behavior control has a positive effect on their intention to choose information technology.*

In this study, "behavioral intention" measures the extent that farmers are motivated to use information technology, along with the efforts they are willing to make to apply it [38]. Many previous studies have shown that the formation of behavioral intention plays a positive role in promoting ultimate behavior [31,34,36,37]. When farmers have positive expectations of the value and benefits of information technology and higher self-confidence in their own capabilities, they perceive less external resistance and feel more favorably about choosing information technology.

Thus, Hypothesis 4 (H4) is proposed:

Hypothesis 4 (H4). *The intention of farmers to choose information technology has a positive effect on their information technology behavior.*

3.2.2. The Moderating Effect of Knowledge Sharing in Transforming Intention into Actual Behavior

Knowledge sharing refers to a process through which knowledge is communicated among individuals or organizations. Most scholars divide it into explicit and tacit knowledge [34]. Explicit knowledge refers to knowledge such as mathematical formulas, diagrams, documents, and data, whereas tacit knowledge refers to knowledge such as experience, intuition, and values [37]. Some studies have shown that knowledge sharing plays an important role in the process of farmers' technology selection [31,34,38,39]. Therefore, improving knowledge sharing channels and strengthening knowledge sharing in general will probably improve farmers' expectations of the possibility of success in using information technology, and, ultimately, in transforming the intention to choose information technology into selection behavior. Thus, Hypothesis 5 (H5) is proposed:

Hypothesis 5 (H5a). *Tacit knowledge sharing has a positive moderating effect on the transformation of farmers' intention to choose information technology into actual behavior.*

Hypothesis 5 (H5b). *Explicit knowledge sharing has a positive moderating effect on the transformation of farmers' intention to choose information technology into actual behavior.*

4. Methods

4.1. Data

The data of this paper come from a field survey conducted by the research group in Shandong Province in May 2021, which used the methods of face-to-face interviews and random sampling. The survey was conducted face-to-face by trained enumerators, with at least one researcher present to ensure the quality of the data collection [4]. The survey involved three towns and their villages. Each township randomly selected two to three villages, and each village randomly selected 20 to 30 apple farmers. To ensure the data quality of the questionnaire and the representativeness of the sample, this study selected Shandong Province as the regional representative of Chinese apple growers. In 2019, Shandong's apple output reached 9,502,300 tons, with an apple planting area of 246.60 thousand hectares; Shandong ranks among the top apple growing areas in the country in terms of output and planting area [5]. A total of 240 questionnaires were distributed and 226 questionnaires were returned. Due to the missing of important variables and inconsistent answers, 14 questionnaires are invalid. The questionnaire had an effective response rate of 94.17%. This process meets the basic research requirements for the sample size and structural equation modeling (SEM) analysis [32,33,35].

The descriptive statistics of the basic characteristics of the sample of 226 rural households are shown in Table 1. In terms of individual characteristics, 54.42% of the farmers were male and 45.58% of the farmers were female. This shows that the ratio of men to women is relatively balanced in the apple industry. The average age of farmers was 58 years old; 8.85% of the farmers were under 45; 63.72% were aged 46 to 65; and 25.66% were over 65. Thus, most farmers were between the ages of 46 and 65. The education among these rural households was generally low: 26.10% of farmers had an elementary school education or below; 60.62% had a junior high school education, and 13.27% had a high school education or above. In terms of family characteristics, the average labor force per household was 2.01; 92.04% of the sample lived in rural households with less than three laborers. The average annual household income in the sample was 63,384.82 yuan; 28.76% of the sample had a household income of 30,000 yuan and below; 51.77% had a household income of 30,000 to 90,000 yuan, and 19.47% had a household income of 90,000 yuan or more. Thus, low-income and middle-income farmers accounted for the largest proportion. In terms of the characteristics of the orchards, land fragmentation was obvious. The scale of apple planting was relatively small, with an average of 0.45 hm² planted per household, and only 23.01% of the farmers with a planting scale of 0.6 hm² or more. Thus, 65.49% of the orchard plots were "very scattered" and "relatively scattered", while 15.04% were in the "general" category and 36.73% were considered "more concentrated" and "centralized".

Table 1. Description of individual characteristics, family characteristics and orchard characteristics of sample farmers.

Item	Category	Percent (%)	Item	Category	Percent (%)
Gender	Male	54.42	Annual household income ($\times 10^4$ CNY)	\leq	28.76
	Female	45.58		3~6	36.73
Age	≤ 35	3.10		6~9	15.04
	36~45	5.75		>9	19.47
	46~55	28.76	Garden area (hm ²)	≤ 0.2	17.26
	56~65	34.96		0.2~0.4	35.84
	>65	25.66		0.4~0.6	23.89
Education	Primary school and below	26.10		>0.6	23.01
	Junior middle school	60.62		Worst	28.76
	Senior high school and above	13.27	Decentralization of land	Bad	36.73
Household scale (person)	1	12.39		Average	15.04
	2	79.65		Well	19.47
	≥ 3	7.96		Best	17.26

4.2. Structural Equation Modeling (SEM)

The SEM has the advantage of being able to handle multiple factors and factor relationships, allowing independent and dependent variables to contain measurement errors. The SEM consists of two parts: one is the measurement model, which reflects the relationships between latent and observable variables; the other is the structural model, which reflects the structural relationships between latent variables. In our study, it is composed of the following equations. Equation (1) is a structural equation that defines the linear relationship between latent variables, and Equations (2) and (3) are measurement equations defining the linear relationship between the latent variables and observed variables.

$$\eta = B\eta + \Gamma\xi + \zeta \quad (1)$$

$$X = \Lambda_x\xi + \delta \quad (2)$$

$$Y = \Lambda_y\eta + \varepsilon \quad (3)$$

where η is the endogenous latent variable and ξ is the exogenous latent variable. The exogenous latent variables in this study are information technology choice intention and information technology choice behavior, and the endogenous latent variables are behavioral attitude, subjective norms, and perceived behavioral control.

B and Γ are the coefficient matrices of η and ξ , respectively; ζ represents the unexplained element; Y and X are the observed variable vectors of η and ξ , respectively; Λ_x and Λ_y represent the correlation coefficient matrix of η and ξ and their observed variables, respectively; and ε and δ represent the residual items, respectively [29,30].

4.3. Variable Description

Based on the TPB and the existing research, the study indicators were adapted from extant research scales [31,34,36,37]. In terms of measurement, we used five-point Likert-like scales to measure the items of the variables and assigned values from 1 to 5 (low to high). In terms of content, the variables were divided into three categories: (1) the respondent's individual characteristics, family characteristics, and orchard characteristics; (2) other related variables under the TPB framework, including the five latent variables, farmers' information technology choice behavioral attitudes, subjective norms, perceived behavioral control, behavioral intention, and behavioral response; and (3) the information technology knowledge-sharing scale, including explicit knowledge sharing and tacit knowledge sharing. The variables, measurement items, and descriptive statistics are shown in Table 2.

4.4. Reliability and Validity Tests

Reliability analysis verifies whether the measurement results are consistent and stable; the higher the reliability, the better the consistency and stability of the sample data. This study used Cronbach's alpha to test the reliability of the data; the results are shown in Table 3. Wu [32] and Wen [35] stated that if Cronbach's alpha is greater than or equal to 0.70, internal consistency is high. From the reliability test results, Cronbach's alpha of information technology behavioral attitude, subjective norms, perceived behavioral control, information technology choice intention, and information technology choice behavior were all between 0.70 and 0.90. Thus, our sample data had good internal consistency and high reliability; this standard is consistent with similar studies [34,36]. In this process, the observed variable ATT3 of behavior and attitude was eliminated because of its low internal consistency.

Table 2. Latent variables, measurement items, and descriptive statistics.

Latent Variable	Measure Item	Mean	Standard Deviation
Attitude toward the behavior (ATT)	ATT1 You are willing to actively learn the information technology in apple production	4.19	1.09
	ATT2 You are willing to take the initiative to obtain information about information technology in apple production	3.86	1.06
	ATT3 You use information technology to pursue higher returns	4.18	0.87
Subjective Norm (SN)	SN1 The importance attached to information technology by the county government or village committee will affect your use of information technology	2.75	1.31
	SN2 Information technology guidance provided by agricultural companies will affect your use of information technology	2.42	1.16
	SN3 The opinions of relatives, friends, and neighbors will affect your use of information technology	3.12	1.33
Perceived Behavioral Control (PBC)	PBC1 You have the professional knowledge and basic skills in the use of information technology	3.04	1.25
	PBC2 You have strong learning ability and can master the use of information technology as soon as possible	3.02	1.21
	PBC3 You have a wealth of information channels and can understand and master information technology related knowledge	2.89	1.15
Behavioral intention (BI)	BI1 You are willing to use information technology	4.07	1.08
	BI2 You are willing to expand the use of information technology	3.56	1.09
	BI3 You are willing to continue to use information technology	3.52	1.02
Behavioral response (BR)	BR1 You have selected information technology in the production process	2.52	1.28
	BR2 You use information technology for a long time	2.32	1.13
	BR3 You use information technology more frequently	2.17	1.04
Knowledge sharing (KS)	KS1 The village committee will provide information technology related guides, instruction manuals and other book knowledge bases	2.51	1.16
	KS2 There are many ways to inquire about information technology related knowledge, such as TV network, etc.	3.18	1.23
	KS3 The village will organize regular visits and learning activities among farmers using information technology	2.78	1.10
	KS4 Whenever you ask big users who use information technology better, they will share their experience without reservation	3.78	1.06

Table 3. Reliability test of measurement variables.

Latent Variable	Observed Variable	Cronbach's Alpha Value
ATT	ATT1	0.805
	ATT2	
SN	SN1	0.806
	SN2	
	SN3	
PBC	PBC1	0.769
	PBC2	
	PBC2	
BI	BI1	0.820
	BI2	
	BI3	
BR	BR1	0.878
	BR2	
	BR3	

Note: Meanings of abbreviations in the column of “Latent variable” and “Observed variable” are shown in the Table 2.

Validity analysis mainly confirms whether the survey data can support the hypotheses and reflect the problem studied. According to relevant research, we used factor analysis to test validity [35,36]. Usually, the value from the KMO (Kaiser-Meyer-Olkin) test should be greater than 0.6 and Bartlett's test of sphericity should be significant at 0.05 [34,36,37]. The results are presented in Table 4. The KMO metric value was 0.793, which is greater than 0.6. The χ^2/df value of Bartlett's test of sphericity was 1506.877, and the p -value was less than 0.01, which passes the 1% significance test and is consistent with standards in similar studies [32,39]. Therefore, the data were suitable for factor analysis.

Table 4. Results of KMO test and Bartlett's spherical test.

Kaiser-Meyer-Olkin Metric for Sufficient Sampling		0.793
Bartlett's Spherical Test	χ^2/df	1506.877
	df	120
	Sig	0.000

We used SPSS AMOS for factor analysis [36]. The results are shown in Table 5. The factor load of each latent variable corresponding to behavioral attitude, subjective norms, perceived behavioral control, technology choice intention, and technology choice behavior was greater than 0.6, indicating that each latent variable was highly representative [32,35]. In addition, the average variance extracted (AVE) corresponding to each latent variable was greater than 0.5, and composite reliability (CR) was greater than 0.7, which indicated that the validity of the sample data was ideal and could reflect the problem studied.

Table 5. Factor load.

	Path		Estimate	AVE	CR
ATI2	←	ATT	0.777	0.673	0.804
ATI1	←	ATT	0.861		
SN4	←	SN	0.694		
SN2	←	SN	0.774	0.586	0.809
SN3	←	SN	0.823		
PBC4	←	PBC	0.676		
PBC2	←	PBC	0.78	0.530	0.772
PBC1	←	PBC	0.725		
BI3	←	BI	0.717		
BI2	←	BI	0.78	0.603	0.819
BI1	←	BI	0.828		
BR3	←	BR	0.817		
BR2	←	BR	0.877	0.712	0.881
BR1	←	BR	0.837		

Note: Meanings of abbreviations in the column of "Path" is shown in the Table 2.

5. Results

5.1. SEM Fit Test

We used SPSS AMOS to test the fit of the model and sample data. The model fitness test indicators and test standards are shown in Table 6. The value of χ^2/df was 2.671, which was less than 3; GFI = 0.940, CFI = 0.937, IFI = 0.939, and NFI = 0.906 were greater than 0.90; PNFI = 0.563 and PCFI = 0.583 were greater than 0.50. Based on the results, the model fit the sample data well.

Table 6. Index and standard of model fitting.

Overall Model Fit Measure Index	Statistical Test Value	Estimated Value	Suggestive Value	Fitting Effect
Absolute index	χ^2/df	2.671	>3.00	ideal
	GFI	0.940	>0.90	ideal
	CFI	0.937	>0.90	ideal
Appreciation index	IFI	0.939	>0.90	ideal
	NFI	0.906	>0.90	ideal
	PNFI	0.563	>0.50	ideal
Contracted index	PCFI	0.583	>0.50	ideal

Note: χ^2/df is the normed chi-square; GFI is the goodness of fit index; CFI is the comparative fit index; IFI is the incremental fit index; NFI is the normed fit index; PNFI is the parsimony adjusted normed fit index; PGFI is the parsimony goodness of fit index.

5.2. Model Estimation Results

To ensure that the quality of the sample data and the reliability and validity of the measured variables met the requirements of academic rigor, we used SEM to test the hypotheses proposed. Table 7 and Figure 2 show that behaviors and attitudes had a significant positive impact on the intention to choose information technology (standardized path coefficient of 0.539), supporting Hypothesis 1. However, the influence of subjective norms on the intention to choose information technology was not significant; thus, Hypothesis 2 was rejected. Perceived behavior control had a significant positive impact on the intention to choose information technology (standardized path coefficient of 0.337); therefore, Hypothesis 3 was supported. Information technology choice intention had a significant positive impact on information technology choice behavior as well (standardized path coefficient of 0.362); therefore, Hypothesis 4 was supported.

Table 7. The path coefficient of the whole model and the test results of model fitting.

	Path		Estimate	S.E.	C.R.	p-Value	Whether to Support the Hypothesis
BI	←	ATT	0.539	0.104	5.524	***	YES
BI	←	SN	0.008	0.014	0.17	0.865	NO
BI	←	PBC	0.337	0.08	3.429	***	YES
BR	←	BI	0.362	0.095	3.447	***	YES

Note: Meanings of abbreviations in the column of “Path” is shown in the Table 2. *** $p < 0.001$.

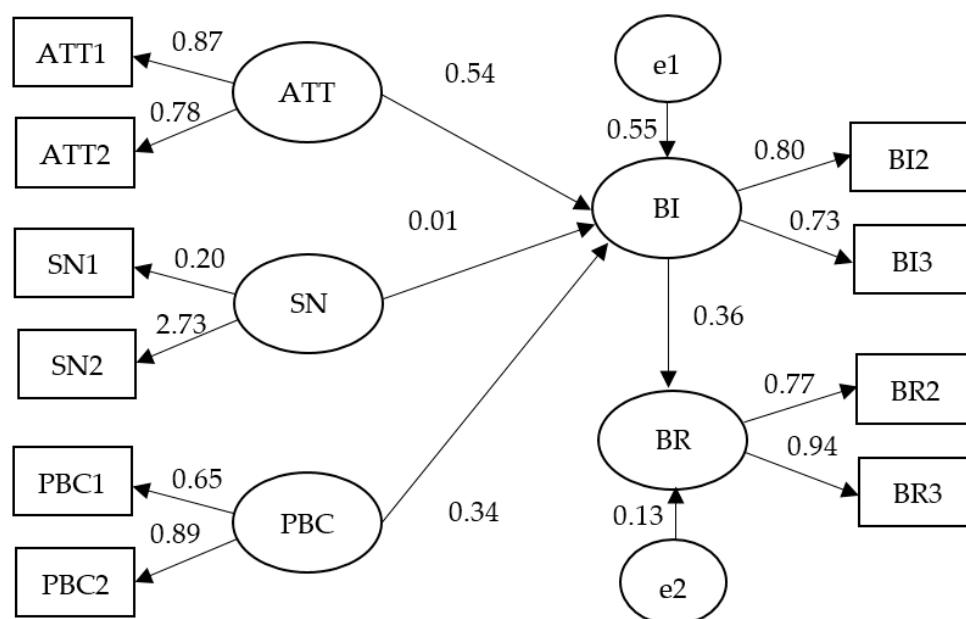


Figure 2. Path diagram of the modified structural equation. Note: Meanings of abbreviations are shown in the Table 2. e1 and e2 are residual and the measurement errors of all observed variable are omitted in this figure.

We used the hierarchical regression analysis method in SPSS to test the moderating effect of tacit knowledge sharing and explicit knowledge sharing [40,41]. To avoid high correlation between the independent variables, we first determined whether there was a multicollinearity problem. Following Wu [28], we relied on two indicators: tolerance and the variance inflation factor (VIF). Generally, if tolerance is less than 0.10 and VIF is greater than 10, there may be multiple commonalities between variables. The results in Table 8 show there was no multivariate commonality among the variables; thus, hierarchical regression analysis could be used.

Table 8. Collinearity diagnosis.

Step	Variable	Tolerance	VIF
The first step of the model	Intention to choose technology	1.000	1.000
	Intention to choose technology	0.931	1.074
The second step of the model	Tacit knowledge sharing	0.892	1.121
	Explicit knowledge sharing	0.907	1.103

In Model 1, with information technology choice behavior as the dependent variable, adding gender, age, years of farming, and educational level to test the effect of the control variables on the dependent variable, the p -value was greater than 0.05, not reaching a significant level. In Model 2, adding information technology choice intention, the results show that the regression coefficient of information technology choice intention on behavior was 0.251, and the p -value was less than 0.001, reaching a significant level. Using Model 2 as the basis, in Model 3, we added tacit knowledge sharing and explicit knowledge sharing; in Model 4, we added technology choice intention and tacit knowledge-sharing interaction terms; in Model 5, we added technology choice intention and explicit knowledge-sharing interaction terms. These results are shown in Table 9. Models 4 and 5 tested the moderating effects of tacit knowledge sharing and explicit knowledge sharing, respectively. The results show that both tacit knowledge sharing and explicit knowledge sharing had a positive moderating effect. The regression coefficient of tacit knowledge sharing on information technology choice behavior was 0.185, and the interaction term of tacit knowledge sharing and information technology choice intention had an effect on information technology. The regression coefficient of selection behavior was 0.160, and its p -value was less than 0.05, reaching a significant level; the regression coefficient of explicit knowledge sharing on information technology choice behavior was 0.172, and the regression coefficient of the explicit knowledge sharing and information technology choice intention interaction terms on information technology choice behavior was 0.133; the p -values were all less than 0.05, reaching a significant level. Thus, H5a and H5b were supported.

Table 9. Regression analysis of the moderating effect of knowledge sharing.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Control variable					
Gender	−0.177 *	−0.153 *	−0.129 *	−0.153 *	−0.124
Age	−0.205 *	−0.173 *	−0.132	−0.138	−0.154
Years of farming	−0.010	−0.028	−0.062	−0.049	−0.060
Education	−0.031	−0.039	−0.047	−0.054	−0.035
Main effect					
Intention to choose technology		0.251 ***	0.191 **	0.271 ***	0.253 ***
Tacit knowledge sharing			0.161 *	0.185 **	
Explicit knowledge sharing			0.158 *		0.172 **
Interaction					
Technology choice intention * Tacit knowledge sharing				0.160 *	
Technology choice intention * Explicit knowledge sharing					0.133 *
ΔF	3.526	6.088	6.859	6.854	6.553
R ²	0.160	0.122	0.180	0.180	0.174

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

By comparing the magnitude of the slopes of the tacit knowledge sharing and explicit knowledge sharing groups, the direction of the effect could be determined [34]. Figure 3 shows that the slopes of the high and low groups of tacit knowledge sharing were both positive, and the slope of the high group was slightly larger than that of the low group, indicating that when the level of tacit knowledge sharing was higher, the intention of farmers to choose information technology was stronger. When the level of tacit knowledge

sharing was low, there was a weaker positive effect on transforming farmers' technology choice intention into behavior.

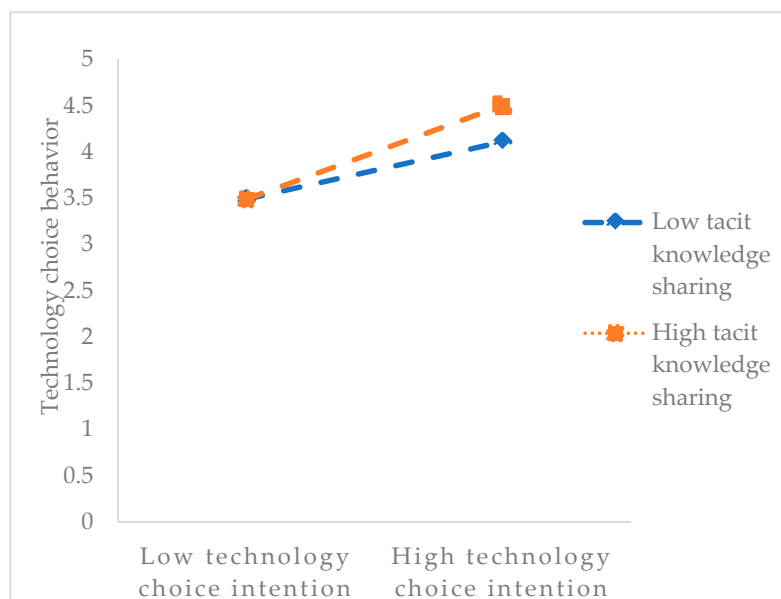


Figure 3. The moderating effect of tacit knowledge sharing on technology choice intention and behavior.

Figure 4 shows that the slopes of the high and low groups of explicit knowledge sharing were both positive, and the slope of the high group was slightly larger than that of the low group, thus indicating that when the level of explicit knowledge sharing was high, it had a strong influence on farmers' intention to choose information technology. When the level of explicit knowledge sharing was low, it had a weaker positive effect on transforming farmers' information technology choice intention into behavior.

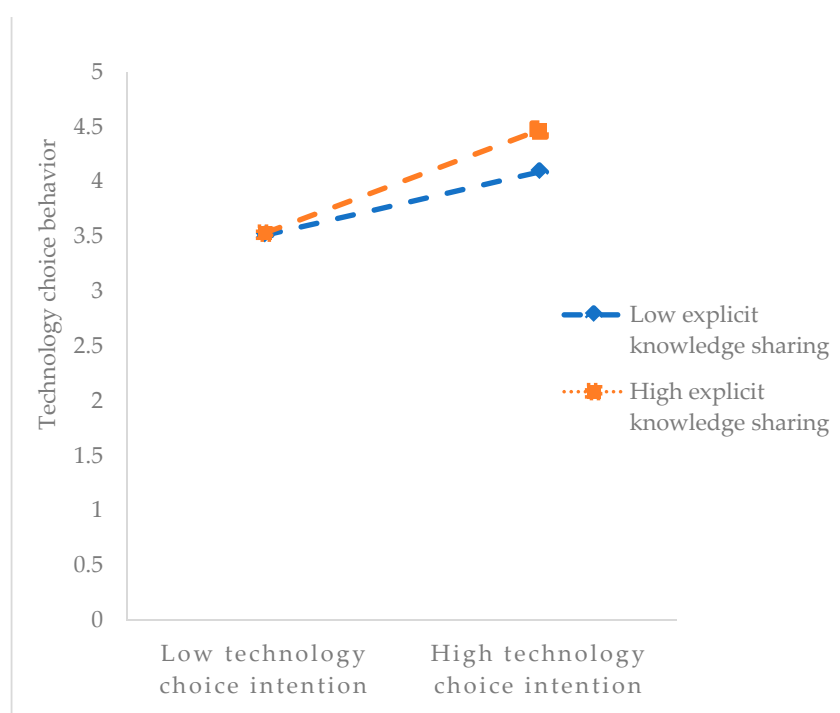


Figure 4. The moderating effect of explicit knowledge sharing on technology choice intention and behavior.

6. Discussion

The study contributes to the agriculture literature by examining the cash crop apple industry and analyzing the differences in behavior among diverse farmers from a micro perspective to clarify the mechanism of information technology choice at the individual farmer level. The results show the following:

(1) Behavioral attitude had a significant positive effect on behavioral intention (standardized path coefficient of 0.539, $p < 0.1\%$), and the degree of influence is the strongest of all variables. When farmers realize that choosing information technology can produce higher benefits, their attitude toward information technology is more positive, which is more conducive to enhancing their behavioral intentions. This is consistent with the conclusion in some studies that the more positive the behavioral attitude, the stronger the behavioral intention [36,37,42].

(2) The influence of subjective norms on information technology choice intentions was positive but not significant. This may be because information technology is an emerging field with high cost and high risk characteristics; thus, the application rate is still very low, and many farmers are still marginalized [38,43,44].

(3) Perceived behavioral control had a significant positive effect on behavioral intention (standardized path coefficient of 0.539, $p < 0.1\%$). Compared with other technologies, the barriers to adopting information technology are higher, and farmers must possess certain professional knowledge to avoid difficulties in the application process. Therefore, the influence of perceptual behavioral control is significant, which is consistent with the conclusion in some studies that farmers who are more active in learning have stronger behavioral intentions [45–47].

(4) Behavioral intention had a significant positive effect on behavioral response (standardized path coefficient of 0.539, $p < 0.1\%$). This indicates that if farmers' behavioral intentions towards information technology are more positive, the greater the possibility of converting intention into actual behavior. This is consistent with the theoretical basis of TPB and has also been confirmed in some studies [36,39,48,49].

(5) Both tacit knowledge sharing and explicit knowledge sharing played a positive moderating role in transforming information technology choice intentions into behavior. This is consistent with some studies that found that the higher the degree of knowledge sharing, the stronger its moderating role in transforming choice intentions into behavior [34,37].

Although our study provides insights into strengthening industry sustainability by improving technology usage, there are several limitations to our study. First, we only used one province, Shandong, in the study sample. In the future, other areas could be examined to determine if the findings apply elsewhere. Second, we focused on information technology from the perspective of individual farmer attitudes, subjective norms, and perceived behavioral control. However, there could be other factors that influence intention, such as technical cost and efficiency. Third, as our study found that knowledge sharing played an important role in the process of farmers choosing information technology, this should be examined in greater depth in the future.

7. Conclusions and Policy Implications

This study applied TPB to data collected through field surveys in Shandong Province, China, and used SEM to empirically analyze the magnitude and direction of the influence of various factors on apple farmers' information technology behavior. We also introduced knowledge sharing into the research as a moderating variable, investigating the role of tacit knowledge sharing and explicit knowledge sharing in the transformation of farmers' information technology choice intention into action. In general, TPB can better explain the regular pattern of farmers' individual information technology choices. Among the cognitive factors that affect farmers' behavioral intentions, behavioral attitudes and perceived behavioral control have a significant positive impact, of which behavioral attitudes play the strongest role. Although subjective norms have a positive impact, their impact is not

significant. Behavioral intention has a positive role in promoting the transformation of individual farmers' cognition to behavioral response. Knowledge sharing plays a positive regulatory role in the corresponding transformation of farmers' behavioral intention to behavior.

Although information technology has become a powerful tool for the development of modern agriculture, information technology in apple production is still in its infancy in China. Based on the above empirical analysis, the following policies are recommended. To promote, modernize, and achieve sustainable development in the apple industry, governments at all levels need to strengthen their roles in the promotion and development of agricultural information technology. In particular, as we found that knowledge sharing had a significant influence, a system of sharing agricultural information technology knowledge needs to be promoted through relevant books, technical demonstrations, and explanations. This approach will help farmers increase their awareness of and confidence in agricultural information technology.

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