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Drivers for the Adoption of Organic Farming: Evidence from an Analysis of Chinese Farmers

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Abstract: Adoption decision is an important topic in organic farming research. In order to understand farmers' decision-making, it is necessary to delve into the factors influencing their behavior. Some studies have used social psychology models to explore the adoption intention of farmers in specific locations regarding organic farming, but there is a lack of investigation into the differences in driving factors for adoption intention among farmers in the pre-organic conversion (conventional), mid-conversion (conversion), and post-conversion (certified) stages, as well as the examination of the relationship between intention and behavior. This study aims to address this issue by examining the driving factors of Chinese farmers' adoption of organic farming practices. We established a theoretical framework based on the Theory of Planned Behavior (TPB) and applied Partial Least Squares–Structural Equation Modeling (PLS-SEM) to analyze intention data collected from 432 farmers and behavior data collected one year later. The study found that attitude, perceived behavioral control, subjective norms, and descriptive norms positively drive the intention to adopt organic farming. In addition to intention being a determinant of behavior, farm size also positively influences behavior. The strength of the impacts of subjective norms on intention and farm size on behavior differs between conventional farmers and conversion farmers. The common driving chain of "attitude → intention → behavior" exists in the organic adoption decision of conventional, conversion, and certified farmers. Our findings suggest that the public sector can attract conventional farmers to transition to organic and stabilize existing practitioners of organic agriculture practices by considering the differences in driving factors when formulating intervention policies.

Keywords: organic farming; drivers; farmers; Theory of Planned Behavior; China

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1. Introduction

Although conventional agriculture provides an increasing amount of food and other products, it is also a major contributor to agricultural chemical pollution, biodiversity loss, greenhouse gas emissions, and soil degradation [1,2]. Concerns about the sustainability of conventional agriculture have led to an interest in more environmentally friendly alternative farming systems. Organic agriculture, a food production method aimed at minimizing harm to ecosystems and human health, is the most popular alternative agriculture globally, with organic agriculture certification implemented in 191 countries. China is a country that implements certified organic agriculture, with an organic farmland area of 2.75 million hectares in 2021 [3]. China is increasingly focusing on organic food production, with the organic industry seen as an important pathway to drive green rural development and increase incomes for small farmers [4]. Despite this emphasis, the organic farmland area in China only accounts for 0.5% of the total agricultural land area, which is far below the global average of 1.6% [3]. This situation calls for an exploration of the driving factors for Chinese farmers to adopt organic farming (OF).

There have been many studies on the importance of different factors driving farmers to adopt OF, mostly in developed countries [5–8]. However, research on the driving factors for the adoption of OF in developing countries is still limited [9–11]. Some literature suggests that financial factors, such as price premiums, public sector payments, or cost savings, are the main reasons driving farmers to adopt OF [12,13]. However, other literature cautions this view and emphasizes the role of non-financial factors [11,14]. This inconsistency suggests that the adoption of OF may be the result of multiple factors, and requires further research on the adoption behavior of OF.

Some scholars argue that the adoption of OF depends on a complex decision-making process, and economic models have weaknesses in fully analyzing the complexities of decision-making. They suggest using theories from social psychology as guidance, in order to understand adoption behavior within a clear framework [15]. In the context of social psychology, the intention to engage in specific behavior is considered a good predictor of actual behavior, with intention being a core concept for understanding the behavior in question [16–18]. Previous literature has employed social psychology models to identify the antecedents of the intention to adopt OF [11,19]. Due to the susceptibility of individual behavior to situational influences, the impact of explanatory variables from the same theoretical model on the intention to adopt may vary across different contexts [11,20,21]. Furthermore, the transition from conventional to certified OF requires a 2–3 year organic conversion period before organic product certification can be obtained, leading to price premiums [22]. Therefore, the differing knowledge and experiences of farmers in the pre-conversion, mid-conversion, and post-conversion stages of OF may result in variations in the strength of the impact of the same explanatory variables on the intention to adopt. The current literature focuses on conventional farmers' intention to adopt OF, lacking discussions on the adoption intention of farmers in the mid- or post-conversion period, ignoring the fact that they may lead to flawed prescriptions.

In addition, few studies have examined whether the intention to adopt OF translates into actual behavior [21]. Some studies have found an intention–behavior gap, where intentions do not effectively predict behavior [23]. For instance, some consumers exhibit a high intention to purchase organic food but do not actually make the purchase [24,25]. Similar to the purchase of organic food, adopting OF is a high-cost pro-environmental type of behavior [26], and there may also be an intention–behavior gap. Therefore, it is necessary to examine the relationship between the intention to adopt OF and actual behavior.

This study aims to fill the research gap by examining the driving factors behind Chinese farmers' adoption of OF. China was chosen as the research case due to its initiation of organic product development and challenges in the slow growth of OF, with only a few studies exploring farmers' adoption decisions regarding OF [27]. The driving factors influencing adoption behavior remain unclear. Moreover, like many developing countries, small-scale farmers are the main agricultural producers in China. Therefore, this country serves as a typical model for analyzing the adoption behavior of farmers in developing countries towards OF. Specifically, we aim to address two questions: which factors are positively correlated with farmers' intention to adopt OF? Is there a positive correlation between intention and behavior?

We adopt the Theory of Planned Behavior (TPB), the most widely applied social psychology theory, as the theoretical framework to address the research question. Based on data collected from 432 farmers in the Xiangxi Tujia and Miao Autonomous Prefecture, Hunan Province, China, we applied Partial Least Squares–Structural Equation Modeling (PLS-SEM) to analyze the driving factors of farmers' intentions to adopt OF and examine the relationship between intention and behavior.

The marginal contributions of this study are reflected in two aspects. Firstly, in contrast to previous literature that primarily focuses on discussing the adoption decisions of conventional farmers in OF, we examine the differences in the driving factors of adoption intention among three subgroups of farmers: conventional, conversion, and certified farmers. This will not only help public sector policymakers better understand farmers' OF adoption behavior, but is also crucial for developing policies to attract conventional farmers and stabilize OF adoption by organic farmers. Secondly, we examine the relationship between intention and behavior in OF adoption, providing empirical evidence for the applicability of the TPB in studying high-cost pro-environmental behavior.

2. Theoretical Framework and Hypotheses

The focus of this study is to explore the driving factors behind farmers' intentions to adopt OF and examine the relationship between intention and behavior. Among the various social psychology models that involve intention and behavior [16–18], the most prominent is TPB. Grounded in the Theory of Reasoned Action (TRA), TPB proposes that behavioral intention is the best predictor and explanatory factor of individual behavior, driven by three independent constructs: attitude, subjective norms (SNs), and perceived behavioral control (PBC) [28]. This theory has been gradually gaining attention in the agricultural field and has been used by many scholars as the main theoretical framework to study various adoption decisions made by farmers [21,29,30]. There are at least three reasons for using TPB as an appropriate theoretical framework to examine OF adoption behavior: firstly, adopting OF is a high-cost behavior that requires farmers to carefully consider, making TPB, based on the assumption of rationality, a preferable theoretical model. Secondly, compared to TRA, TPB incorporates the variable of PBC, which helps explain the influence of factors not completely under volitional control in behavior [31]. This is suitable for incorporating the impact of difficulties or potential constraints perceived by farmers in adopting organic agriculture into the research model. Thirdly, TPB allows for the consideration of other factors in the decision-making process [25,32,33], to improve the accuracy of the model's predictions. Considering that there is considerable empirical evidence supporting the influence of descriptive norms, farm size, or public policies on farmers' decision-making [34,35], the aforementioned seven constructs are modeled in our framework as direct or indirect driving factors of adoption behavior. The research framework is shown in Figure 1.

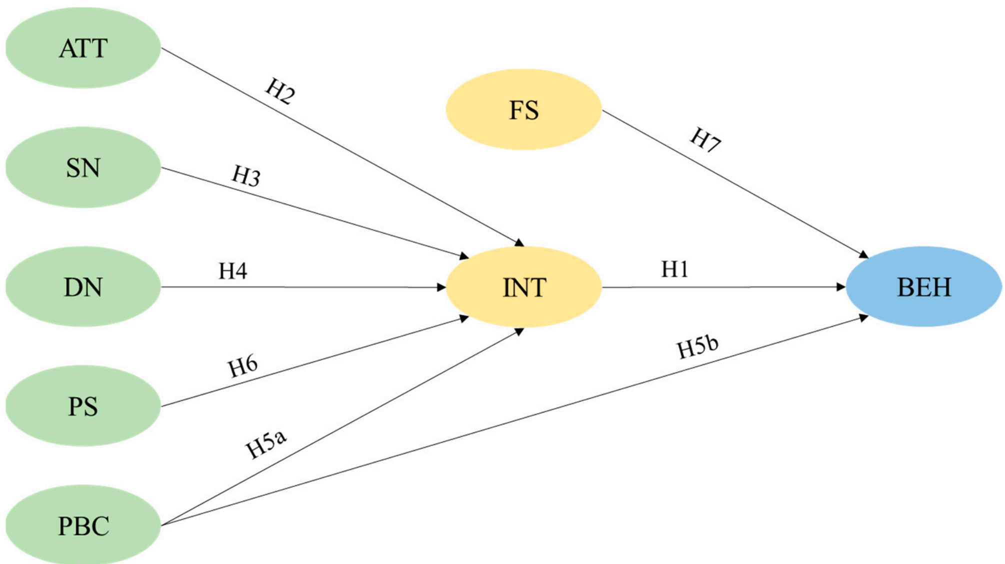

Figure 1. The research framework. ATT = attitude; SN = subjective norm; DN = descriptive norm; PS = policy satisfaction; PBC = perceived behavioral control; INT = intention to adopt organic farming; FS = farm size; BEH = organic farming adoption behavior.

Next, we state the hypotheses obtained from the relevant literature.

2.1. Intention

The concept of intention (INT) pertains to the underlying motive that drives an individual's actions, reflecting the extent to which the individual is inclined to exert effort in carrying out a certain behavior. The present study operationalizes intention as the self-evaluation of farmers' willingness to make an effort to engage in OF. TRA suggests that intention, rather than attitude, is the primary predictor of actual behavior [16]. According to Ajzen [28], intention is indicative of the internal causation of conduct, and a stronger intention increases the likelihood of the activity being manifested. Intention is widely recognized as a powerful predictor of technology adoption [36]. Similarly, in voluntary situations, such as adopting OF, intention is considered the best predictor of behavior [19–21]. In the current literature background, we propose the first hypothesis as follows:

H1. *Intention positively drives organic farming adoption behavior.*

2.2. Attitude

Attitude (ATT) is to a learned tendency to react positively or negatively towards an item in particular, whereas intention is the outcome of attitude [16]. A positive attitude will lead to a higher intention [28]. In this study, attitude is defined as the positive or negative evaluation that farmers hold towards adopting OF [37]. Hou and Hou [30] found that the more positive farmers' attitudes toward low-carbon production, the stronger their intention to adopt low-carbon production. The research by Cakirli Akyüz and Theuvsen [19] and Issa and Hamm [21] found that positive attitudes positively drive farmers' intentions to adopt OF. Therefore, this study expects that:

H2. *Attitude positively drives the intention to adopt organic farming.*

2.3. Subjective Norms

Subjective norms (SNs) are used to measure the social pressure individuals feel when deciding whether or not to do something [28]. For farmers, this often manifests as the influence of family, friends, organizational groups, and societal opinions on their decision-making [30,33]. Kaufmann et al. [14] found that SN have a positive impact on farmers' decisions to adopt OF. Cakirli Akyüz and Theuvsen [19] found that SN are driving factors for organic farmers to continue adopting OF and for conventional farmers to adopt OF. Furthermore, previous research conducted by Läpple and Kelley [5], Tama et al. [38], and Van et al. [39] has shown similar findings, indicating that SNs exert a favorable influence on farmers' inclination to embrace OF. Therefore, this paper proposes the hypothesis:

H3. *Subjective norms positively drive the intention to adopt organic farming.*

2.4. Descriptive Norms

Although SN can partially explain intention toward a behavior, empirical evidence suggests that their impact may be limited [33]. However, it is undeniable that social influence is the most common factor driving individual behavior. Given the importance of other people's influence, and because previous studies have found that SNs perform poorly in explaining farmers' intentions to adopt OF, we also examined another form of social influence: descriptive norms (DNs). Descriptive norms refer to the effect of the behavior of reference groups around an individual [40]. It is similar to the observability factor in the Innovation Diffusion Theory (IDT), where the observability of a new technology is positively related to its adoption rate [41]. Unlike subjective norms, descriptive norms tend to perceive the degree to which a behavior is being executed, while subjective norms tend to perceive pressure from others [32]. In the context of healthy eating [32], green travel [42], drinking [43], and practicing yoga [44], researchers have found that descriptive norms have a positive impact on intention, but Povey et al. [32] and Rimal et al. [44] showed that it has no direct impact on behavior. In this study, descriptive norms are defined as farmers' perceptions of the adoption of organic farming technology behavior by reference groups around them. In this sense, if they know that others are doing the same, farmers are more likely to form an adoption intention. Based on this, we make the following hypothesis:

H4. *Descriptive norms positively drive the intention to adopt organic farming.*

2.5. Perceived Behavioral Control

Perceived behavioral control (PBC) refers to an individual's perception of the ease or difficulty of implementing a behavior [28]. In this paper, we define PBC as farmers' confidence in their ability to engage in OF. Issa and Hamm [21] found that PBC has a positive impact on Syrian fruit and vegetable farmers' intentions and behaviors to adopt OF, and that farmers with higher levels of education have a stronger willingness to adopt OF. Kaufmann et al. [14] compared diffusion simulations of organic production in Latvia and Estonia and found that changing PBC (e.g., through changes in social influence and subsidies) or combining PBC with SN (e.g., by increasing farm advisors) can increase the proportion of farmers adopting OF. Andow et al. [11] also found that the stronger the producer's perceived control over organic conversion, the higher their intention to convert to OF. In other fields, many studies have shown that perceived behavioral control not only affects intention but also behavior [31,45–47]. Therefore, we anticipate:

H5a. *Perceived behavioral control positively drives the intention to adopt organic farming.*

H5b: *Perceived behavioral control positively drives the behavior of adopting organic farming.*

2.6. Satisfaction with Support Policies

The function of support policies from the public sector is of utmost importance in facilitating the advancement of organic farming [48]. For instance, subsidy policies can increase farmers' incomes [35,49], while technical support enables farmers to quickly grasp organic production techniques [50]. Generally, the higher the satisfaction of farmers with OF policies, the more willing they are to adopt OF practices [51]. Based on these observations, we propose the following hypotheses:

H6. *The higher the level of farmers' satisfaction with organic farming support policies, the higher the intention to adopt organic farming.*

2.7. Farm Size

Usually, the scale can generate economies of scope on farms [34]. Studies have found that farm size (FS) influences farmers' adoption of organic farming [6,52]. Karipidis and Karypidou's [53] review suggested that farm size affected farmers' management strategies and subsequently, their adoption of organic farming, but this impact varies by country, region, and culture. According to Sriwichailamphan's [9] study conducted in Thailand, there is evidence suggesting that farmers with greater farm sizes exhibit a higher propensity to engage in OF. Additionally, farm size is an important indicator of farmers' wealth [21]. Higher levels of farmer wealth help them overcome difficulties in OF and engage in technological innovations for OF [50], which facilitates the implementation of organic production behaviors. Based on this, we propose the following hypothesis:

H7. *Farm size positively drives farmers' behavior in adopting organic farming.*

3. Materials and Methods

3.1. Questionnaires and Measurements

To examine the correlation between intention and behavior, the questionnaire survey in this investigation was divided into two distinct stages (see Table 1). The initial stage questionnaire comprised two distinct sections. The first section measured intention and its six influencing factors in the research model, including intention (3 items), attitude (2 items), subjective norms (3 items), descriptive norms (3 items), PBC (4 items), satisfaction with support policies (6 items), and farm size (1 item). Among them, the first six variables used a Likert 5-point scale. Farm size was a specific numerical value (unit: mu, 1 mu = 1/15 ha), and was assigned a value of 1–5. If the farm size was less than 2/15 ha, it was assigned a value of 1; if 2/15 ha $\leq$ farm size < 1/3 ha, it was assigned a value of 2; if 1/3 ha $\leq$ farm size < 2/3 ha, it was assigned a value of 3; if 2/3 ha $\leq$ farm size < 4/3 ha, it was assigned a value of 4; if the farm size was 4/3 ha or more, it was assigned a value of 5. The second section mainly contained the demographic characteristics of the respondents, including gender, age, education, and family annual income. The questionnaire items in this stage were revised based on existing research [10,21,54,55].

The second stage questionnaire measured the actual behavior of farmers, with the item being the area of land invested in OF by the farmers interviewed in the first stage, and assigned values based on the proportion of organic farmland to their total farmland area. 0% was assigned a value of 1; 0% < proportion < 25% was assigned a value of 2; 25% $\leq$ proportion < 50% was assigned a value of 3; 50% $\leq$ proportion < 75% was assigned a value of 4; and proportion $\geq$ 75% was assigned a value of 5.

Table 1. Questionnaire.

Construct		Items	Stage
Intention	int1	You intend to engage in organic farming on your own land (including renting someone else's land or acquiring it through a transfer) next year.	Stage1
	int2	You will adopt organic farming on your own farmland next year (including renting someone else's land or acquiring it through a transfer).	
	int3	The ratio of organic farmland area to total farmland area is intended by the farmers for organic production.	
	int4	The scale (area) of organic production you plan to engage in on your own agricultural land next year (including renting someone else's land or acquiring it through a transfer) is _____ mu. (1 mu = 1/15ha)	
Farm size	fs	The total area of agricultural land in your household (including land rented from others or obtained through transfer) is ____ mu. (1 mu = 1/15 ha)	Stage1
Attitude	att1	It's a good idea to adopt organic farming on your own (including renting someone else's land or acquiring it through a transfer) farmland next year.	Stage1
	att2	Organic farming on your own (including renting someone else's land or acquiring it through a transfer) farmland will make you happy next year.	
Subjective norms	sn1	Your family supports you in practicing organic farming on your own (including renting someone else's land or acquiring it through a transfer) farmland next year.	Stage1
	sn2	Your neighbors support organic farming on your own (including renting someone else's land or acquiring it through a transfer) farmland next year.	
	sn3	Your relatives and friends support you in adopting organic farming on your own (including renting someone else's land or acquiring it through a transfer) farmland next year.	
Descriptive norms	dn1	You have neighbors who will be adopting organic farming next year on farmland their owns (including renting it from someone else or acquiring it through a transfer).	Stage1
	dn2	You have relatives or friends who will be adopting organic farming on their own (including renting someone else's land or acquiring it through a transfer) farmland next year.	
	dn3	Your neighborhood will be home to organic product companies next year.	
Perceived behavioral control	pbc1	If you are engaged in organic farming on your own (including renting someone else's land or acquiring it through transfer) farmland next year, you (your family) have the ability to properly deal with the technical aspects of organic farming.	Stage1
	pbc2	If you are engaged in organic farming on your own (including renting someone else's land or acquiring it through a transfer) farmland next year, you (your family) are in a position to handle the marketing of your organic products.	
	pbc3	If you engage in organic farming on your own (including renting someone else's land or acquiring it through a transfer) farmland next year, you (your family) will be able to comply with the standard requirements for organic farming.	
	pbc4	If you engage in organic farming on your own (including renting someone else's land or acquiring it through a transfer) farmland next year, you (your family) can afford the cost of organic farming.	

Table 1. *Cont.*

Construct		Items	Stage
Policy satisfaction	ps1	You are satisfied with your local (county and township) government's policy of subsidizing organic farming.	Stage1
	ps2	You are satisfied with your local (county and township) government's training policy on organic farming.	
	ps3	You are satisfied with your local (county and township) government policies regarding technology and information provision for organic farming.	
	ps4	You are satisfied with your local (county and township) government's organic farming loan policy.	
	ps5	You are satisfied with your local (county and township) government's policies regarding cooperation in organic farming.	
	ps6	In general, you are satisfied with your local (county and township) government's policy on organic farming.	
Behavior	beh	The proportion of organic farmland to their total farmland area.	Stage2
	beh1	In the past year, the amount of your family's farmland in organic production on your own property (including renting from others or acquired through land transfers) was _____ mu (1mu = 1/15ha).	

Note: For int3 (proportion = int4/fs), a value of 1 was assigned for 0% proportion, while values of 2, 3, 4, and 5 were assigned in equal quartiles for proportions greater than 0% and less than or equal to 100%, from smallest to largest. The demographic variables, as well as the assignment of *beh*, are described in the main text and will not be repeated in this section.

3.2. Sampling and Data Collection

This study selected four counties, namely Guzhang, Baojing, Huayuan, and Yongshun, in Xiangxi Tujia and Miao Autonomous Prefecture as the research area, located in the northwest region of Hunan Province in central China (see Figure 2). The reason for choosing these four counties is that they are all certified poverty alleviation counties for organic products in China, and they have favorable natural conditions for the development of organic agriculture. The local governments support the development of organic agriculture to help farmers escape poverty. Moreover, these local governments are considering further supporting the promotion of organic agriculture and need to understand the factors driving farmers' adoption of OF. From June to September 2020, we conducted a questionnaire survey on farmers' intentions to adopt OF. According to the total number of organic farming households (including conversion and certified farmers) obtained from the local government agricultural departments in the four counties, a total of 386 households were included (124 in Guzhang, 144 in Baojing, 41 in Huayuan, and 77 in Yongshun). According to the recommendations of Cochran [56] and Singh and Masuku [57], with a 95% confidence level, the minimum sample size of organic farmers in each county was determined using a sample size calculator (62 in Guzhang, 72 in Baojing, 20 in Huayuan, and 38 in Yongshun), and in the same proportion to determine the sample size of conventional farmers. Considering the possibility of invalid questionnaires, 120% of the minimum sample size was distributed, resulting in a total of 476 questionnaires. Then, a stratified proportional sampling method was used to sample organic farmers in each county's townships, and structured survey questionnaires were distributed to voluntary participants to collect data. Conventional farmers were also sampled around the organic farming sample. The selection of conventional farmers adjacent to organic farmers as sampling subjects is because these farmers should have considered whether to adopt OF techniques and can provide valid information. All respondents in this study were household heads, because they usually play a dominant role in production decision-making in farming households. Invalid questionnaires with obvious contradictions, incomplete responses, or obvious patterns were excluded. Finally, 450 valid questionnaires were collected, with an effective rate of 95%. One year later, we conducted follow-up visits to the 450 farmers who were interviewed and provided valid questionnaires in the first stage through a combination of household visits and telephone surveys to collect data on the conversion of intention into behavior. A total of 432 valid questionnaires were obtained, with an effective rate of 96%. The reason for choosing a one-year interval for predicting the intention–behavior relationship is mainly due to concerns that the effectiveness of the prediction may be affected by changes in policy circumstances over a long time interval.

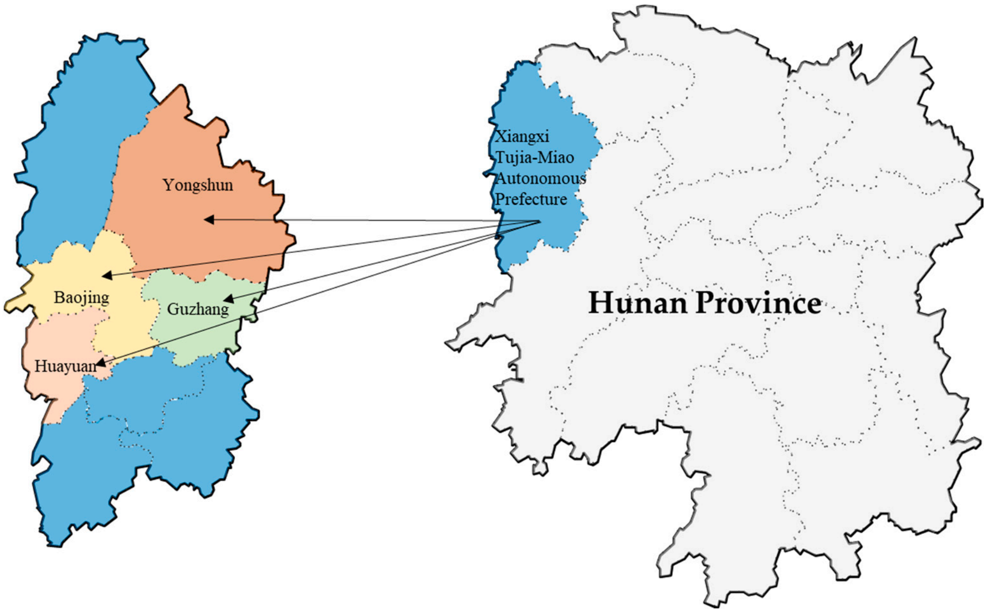

Figure 2. Research area.

According to the "ten times" rule proposed by Hair et al. [58] and Chin [59] for PLS-SEM, which suggests that the minimum sample size required for a structural model is ten times the largest path or relationship coefficient, our model requires a minimum sample size of 60 (as the maximum structural path or relationship coefficient is 6, meaning a minimum of 60 respondents is needed). Therefore, the sample size of 432 exceeds the required number according to this rule, and a larger sample size can enhance the estimation accuracy of PLS-SEM [60]. Thus, the sample size of this study has sufficient statistical power.

3.3. Data Analysis Methods

We first conducted descriptive statistical analysis on the 432 valid data using SPSS 23.0 software. Subsequently, the research model was empirically tested using PLS-SEM in the SmartPLS 4 software [61]. PLS-SEM is a statistical method based on regression, that relies on a pre-specified network of relationships between constructs and their measurement indicators. According to Hair et al. [60], this method is appropriate for examining the associations among several independent factors and one or more dependent variables. Furthermore, PLS-SEM has advantages, such as suitability for small sample sizes, not requiring the normal distribution of analyzed data, and using constructs with fewer indicators [60]. The method has been widely used in research related to intention, behavior, and the TPB [25,45,46]. Hair et al. [60] pointed out that PLS-SEM is an effective statistical evaluation method for determining key driving factors or predicting key target constructs. The purpose of this research is to identify key drivers affecting farmers' intentions and behavior in OF, therefore, using PLS-SEM to evaluate the model is reasonable.

Model evaluation can be mainly divided into three steps. The first step is to assess the reliability and validity of the measurement model. The second step is to evaluate the structural model in order to test the theoretical assumptions made earlier and identify the driving factors behind farmers' adoption of OF. In the third step, farmers were categorized into three subgroups of conventional, conversion, and certified farmers, according to whether they were in pre-, mid-, or post-organic conversion for multi-group analysis. This analysis aims to determine the differences in the strength of the influence of the driving factors among these groups.

4. Results

4.1. Descriptive Statistics

Table 2 provides an overview of the descriptive statistics of the respondents who completed the two-phase questionnaire survey. A total of 432 participants were included in this study, consisting of 236 conventional farmers, 82 conversion farmers, and 114 certified farmers. The overall gender ratio was approximately 2:1, with a higher proportion of males. In terms of age, the 41–50 age group had the highest representation in all three groups. Compared to conventional farmers, organic farmers had a higher proportion of individuals with a college degree or above. Regarding household annual income, organic farmers had a higher proportion of individuals earning over 100,000 ¥ (1 ¥ ≈ 0.140 $) compared to conventional farmers. Between 2020 and 2021, conventional farmers converted 192.67 hectares of farmland into organic farms, and both conversion and certified farmers experienced expansion in the scale of their organic farms.

Table 2. Descriptive statistics.

Variable	Category	Overall (N = 432, 100%)	Conventional Farmers (N = 236, 54.6%)	Organic Farmers	
				Conversion Farmers (N = 82, 19.0%)	Certified Farmers (N = 114, 26.4%)
Gender	Male	289 (66.9%)	164 (69.5%)	56 (68.3%)	69 (60.5%)
	Female	143 (33.1%)	72 (30.5%)	26 (31.7%)	45 (39.5%)
Age	≤30	28 (6.5%)	13 (5.5%)	8 (9.8%)	7 (6.1%)
	31~40	89 (20.6%)	44 (18.6%)	29 (35.4%)	16 (14.0%)
	41~50	151 (35.0%)	72 (30.5%)	31 (37.8%)	48 (42.1%)
	51~60	126 (29.2%)	78 (33.1%)	11 (13.4%)	37 (32.5%)
	≥61	38 (8.8%)	29 (12.3%)	3 (3.7%)	6 (5.3%)
Education	Primary or below	133 (30.8%)	80 (33.9%)	14 (17.1%)	39 (34.2%)
	Junior high school	139 (32.2%)	87 (36.9%)	21 (25.6%)	31 (27.2%)
	High school	90 (20.8%)	49 (20.8%)	23 (28.0%)	18 (15.8%)
	College or higher	70 (16.2%)	20 (8.4%)	23 (29.3%)	26 (22.8%)
Annual household income	<10,000 ¥	7 (1.6%)	6 (2.5%)	0 (0.0%)	1 (0.9%)
	10,000 ¥~50,000 ¥	149 (34.5%)	107 (45.3%)	14 (17.1%)	28 (24.6%)
	50,000 ¥~100,000 ¥	130 (30.1%)	76 (32.2%)	18 (22.0%)	36 (31.6%)
	100,000 ¥~150,000 ¥	59 (13.7%)	21 (8.9%)	21 (25.6%)	17 (14.9%)
	>150,000 ¥	87 (20.1%)	26 (11.0%)	29 (35.4%)	32 (28.1%)
The total farm size in 2020 (ha)		8237.91 (100%)	860.30 (10.4%)	3020.79 (36.7%)	4356.82 (52.9%)
Including: organic farm size (ha)		4874.05 (100%)	0 (0.0%)	1471.20 (30.2%)	3402.85 (69.8%)
The organic farm size in 2021 (ha)		5897.79 (100%)	192.67 (3.3%)	1766.33 (29.9%)	3938.80 (66.8%)

4.2. Measurement Model Assessment

Initially, an assessment was conducted to examine the reliability and validity of the measuring model. This assessment encompassed the examination of internal consistency, convergent validity, and discriminant validity. The assessment of internal consistency was conducted using Cronbach's alpha (CA), whereas the evaluation of convergent validity involved examining factor loadings, composite reliability (CR), and AVE [59,60]. All CA for the constructs were above 0.7 (Table 3), indicating high reliability of the model. The factor loading and CR all exceeded the threshold of 0.7, and AVE were above 0.5, as recommended by Hair et al. [60]. This indicates that the model exhibits strong convergent validity.

Table 3. Internal consistency and convergent validity of the measurement model.

Construct	Item	Factor Loading	CA	CR	AVE
Attitude (ATT)	att1 att2	0.925 0.904	0.805	0.911	0.837
Subjective norms (SN)	sn1 sn2 sn3	0.875 0.873 0.909	0.864	0.916	0.785
Perceived behavioral control (PBC)	pbc1 pbc2 pbc3 pbc4	0.794 0.800 0.729 0.746	0.768	0.852	0.590
Policy satisfaction (PS)	ps1 ps2 ps3 ps4 ps5 ps6	0.839 0.855 0.874 0.843 0.896 0.920	0.937	0.950	0.760
Descriptive norms (DN)	dn1 dn2 dn3	0.872 0.901 0.712	0.771	0.870	0.693
Intention (INT)	int1 int2 int3	0.913 0.921 0.828	0.865	0.918	0.789
Farm size (FS)	fs	1.000	1.000	1.000	1.000
Behavior (BEH)	beh	1.000	1.000	1.000	1.000

The Fornell–Larcker criterion [62] is an effective method for assessing discriminant validity. This method compares the square root of the AVE of each construct with the correlations between constructs to test the discriminant validity of the model [59,60]. The comparison results of the values in Table 4 indicate that the model has high discriminant validity. Additionally, the model was tested using the heterotrait–monotrait (HTMT) ratio of correlations method. This approach evaluates the proportion of the mean correlations among distinct constructs in comparison to the mean correlations among identical constructs. The HTMT values for all constructs in the model were found to be less than 0.85 (see Table 5) [60], further indicating good discriminant validity of the model. Based on these findings, a test for multi-collinearity was conducted on the model, with the maximum variance inflation factor (VIF) being 4.258, indicating the absence of multicollinearity in the model.

Table 4. Discriminant validity of the measurement model (Fornell–Larcker criterion).

	ATT	BEH	DN	FS	INT	PBC	PS	SN
ATT	0.915							
BEH	0.315	1.000						
DN	0.387	0.240	0.832					
FS	0.207	0.355	0.116	1.000				
INT	0.540	0.602	0.406	0.281	0.888			
PBC	0.549	0.383	0.378	0.271	0.511	0.768		
PS	0.361	0.255	0.321	0.117	0.326	0.415	0.872	
SN	0.530	0.301	0.465	0.204	0.484	0.606	0.353	0.886

Table 5. Discriminant validity of the measurement model (HTMT).

	ATT	BEH	DN	FS	INT	PBC	PS	SN
ATT								
BEH	0.350							
DN	0.499	0.273						
FS	0.229	0.355	0.133					
INT	0.645	0.648	0.497	0.302				
PBC	0.698	0.434	0.495	0.310	0.623			
PS	0.415	0.263	0.378	0.121	0.358	0.489		
SN	0.631	0.320	0.571	0.218	0.554	0.739	0.394	

4.3. Structural Model Assessment

The findings of the validation of the theoretical framework are summarized in Table 6. The results indicate that attitude (β = 0.290, p = 0.000), SN (β = 0.123, p = 0.046), and PBC (β = 0.202, p = 0.000) influence intention in positive ways. The three factors that drive intention in the classical TPB model are supported in this study. Furthermore, it is seen that descriptive norms exhibit a positive effect on intention (β = 0.145, p = 0.003), but policy satisfaction does not demonstrate a significant influence on intention (β = 0.047, $p > 0.05$). Intention emerges as the most influential driving component of behavior, as evidenced by a positive beta coefficient of 0.513 (p = 0.000), followed by farm size (β = 0.193, p = 0.000), while PBC does not have a significant impact statistically (β = 0.068, $p > 0.05$).

Table 6. Results of the structural model analysis (bootstraps = 5000).

Relationship	β	T-Statistics	*p*-Values	Result	f^2
ATT→INT	0.290	5.564	0.000	Supported	0.085
SN→INT	0.123	1.992	0.046	Supported	0.013
PBC→INT	0.202	3.502	0.000	Supported	0.036
PS→INT	0.047	1.044	0.296	Rejected	0.003
DN→INT	0.145	2.947	0.003	Supported	0.025
PBC→BEH	0.068	1.584	0.113	Rejected	0.006
INT→BEH	0.513	13.531	0.000	Supported	0.317
FS→BEH	0.193	4.342	0.000	Supported	0.056

Note: β = Path coefficient.

This coefficient assesses the predictive ability of the model [60], with an R^2 value of 0.394 for intention and 0.404 for behavior. According to the criteria proposed by Chin [63], the model achieves moderate explanatory strength for both intention and behavior. In addition, we evaluated the effect size f^2, the results of which are shown in Table 6. Based on Cohen's [64] established criteria, effect sizes can be categorized as small, medium, or large when the values of f^2 are 0.02, 0.15, and 0.35, respectively. Based on this standard, the INT→BEH effect was of medium size, while the effects of ATT→INT, PBC→INT, DN→INT, and FS→BEH were small. The effects of SN→INT, PS→INT, and PBC→BEH could be considered negligible. In conclusion, we assumed that H1, H2, H3, H4, H5a, and H7 are valid, while H5b and H6 are not.

Finally, we evaluated the predictive validity of the model using the Blindfolding procedure. According to the criterion of Hair et al. [60], a Q^2 value greater than 0 indicates that the model possesses predictive relevance for an endogenous construct. In the event that the value of Q^2 is equal to or less than 0, it can be inferred that the model exhibits a deficiency in its ability to provide predictive relevance. In the model of this paper, the Q^2 of INT and BEH are 0.302 and 0.396 respectively, indicating that the model has predictive relevance. In addition, Hair et al. [60] have also highlighted the utility of the q^2 effect size in assessing the relative influence of predictive relevance. The q^2 values of 0.02, 0.15, and 0.35, respectively, signify the predictive relevance of the exogenous construct for the endogenous construct, with small, medium, or large effect sizes. The q^2 effect sizes are shown in Table 7, where INT→BEH is a medium effect, and ATT→INT, PBC→INT, and FS→BEH are small effects.

Table 7. q^2 effect sizes.

	INT	BEH
ATT	0.057	
SN	0.007	
PBC	0.020	0.005
PS	0.000	
DN	0.016	
FS		0.053
INT		0.308

4.4. Multi-Group Analysis

To better reveal the drivers of farmers' organic farming adoption before, during, and after the conversion, we divided the farmer population into three subgroups: conventional group, conversion group, and certified group. For the sake of comparison, we used the conventional group as the reference group, and the outcomes of the multi-group analysis are presented in Table 8.

Table 8. Multi-group analysis.

Paths	Conventional Farmers			Conversion Farmers			Diff1.	Certified Farmers			Diff2.
	γ	T-Sta.	Re.	γ	T-Sta.	Re.		γ	T-Sta.	Re.	
ATT→INT	0.325 *	4.660	S	0.352 *	2.539	S	−0.027	0.395 *	2.755	S	−0.070
SN→INT	0.180 *	2.462	S	−0.350	1.920	R	0.530 *	0.095	0.929	R	0.085
PBC→INT	0.091	1.197	R	0.358 *	2.033	S	−0.267	0.133	1.039	R	−0.042
PS→INT	0.014	0.254	R	0.009	0.062	R	0.005	−0.053	0.517	R	0.067
DN→INT	0.139 *	2.228	S	0.258	1.534	R	−0.120	0.103	1.502	R	0.036
INT→BEH	0.314 *	5.950	S	0.616 *	3.977	S	−0.301	0.303 *	2.121	S	0.011
PBC→BEH	0.038	0.625	R	−0.131	0.912	R	0.169	−0.047	0.397	R	0.085
FS→BEH	0.110	1.682	R	−0.160 *	2.775	S	0.270 *	0.191	1.488	R	−0.081

Note: γ = Path coefficient; T-sta. = T-statistics; Re. = results; Diff1. = conventional farmers–conversion farmers; Diff2. = conventional farmers–certified farmers; * means $p < 0.05$; S = supported, R = rejected.

For the conventional group, attitude ($\gamma = 0.325$, $p < 0.05$), subjective norms ($\gamma = 0.180$, $p < 0.05$), and descriptive norms ($\gamma = 0.139$, $p < 0.05$) positively drive their intention to adopt OF, and intention positively drives the adoption behavior ($\gamma = 0.314$, $p < 0.05$). For the conversion group, intention is positively driven by attitude ($\gamma = 0.352$, $p < 0.05$) and perceived behavioral control ($\gamma = 0.358$, $p < 0.05$), and behavior is positively influenced by intention ($\gamma = 0.616$, $p < 0.05$), but farm size ($\gamma = -0.160$, $p < 0.05$) has a negative impact on behavior. For the certified group, intention is only positively influenced by attitude ($\gamma = 0.395$, $p < 0.05$), and behavior is only positively influenced by intention ($\gamma = 0.303$, $p < 0.05$), forming an "attitude→intention→behavior" chain of behavior pattern.

The results of the hypothesized relationship test between the conventional and certified groups were not statistically different (see Table 8, Diff2. column). However, there were differences in the relationship between the conventional farmers and the conversion farmers in terms of SN to intention (Diff1 = 0.530, $p < 0.05$) and farm size to behavior (Diff1 = 0.270, $p < 0.05$). Through the integration of path coefficients, it becomes evident that the impact of SN on intention and the influence of farm size on behavior exhibit contrasting patterns in conventional and conversion farmers.

5. Discussion

We used the TPB to investigate the adoption of OF among Chinese farmers. Path analysis of cross-sectional data collected from 423 respondents revealed that attitude, PBC, and subjective norms had significant influences on intention. These findings support the applicability of the classical TPB as a theoretical foundation for studying the intention to adopt OF [5,21]. It is worth noting that the impact of subjective norms on intention was relatively small, possibly because only a small proportion of farmers have adopted OF, and its prevalence is still low, thus lacking effective social pressure. Additionally, this study found that descriptive norms positively drive farmers' intentions to adopt OF, which aligns with the findings of Van et al. [39]. They found that farmers are more willing to adopt OF when they have friends or relatives who have already adopted it, as it increases their confidence in profiting from OF and facilitates the imitation and learning of relevant techniques. This reflects the influence of observability on technology adoption behavior [41], indicating that knowing others are doing it increases the likelihood of farmers forming adoption intentions. Surprisingly, although satisfaction with policies positively drives intention, it is not statistically significant. This may be because most farmers hold a neutral attitude towards existing supportive policies, which does not imply their ineffectiveness. Our survey found that the supportive policies in the research area are not universal but rely on competition to receive public sector payments, benefiting only a small fraction of farmers.

Multi-group analysis shows that there is no statistically significant difference between the driving factors of conventional farmers and certified farmers' intentions, which may be due to the fact that farmers in these two groups are accustomed to their respective production methods, resulting in relatively stable behavior. However, there is a significant difference in the SN→INT relationship between conventional farmers and conversion farmers, indicating that conventional farmers are more concerned about the pressure from others to adopt OF than conversion farmers. This is inconsistent with the views of Yazdanpanah et al. [33] and Andow et al. [11], whose studies show that social pressure does not affect the adoption intention of conventional farmers. This inconsistency may be due to different situations, but further verification is needed. Although there is no statistically significant difference in other driving factors on intention between groups, descriptive norms have a greater impact on the intention of conventional farmers, and PBC is more likely to affect the intentions of conversion farmers. For conventional farmers who have no experience in adopting OF, the adoption behavior of important others or nearby organic demonstration sites may have a significant impact on their adoption intentions. On the other hand, conversion farmers, facing difficulties such as insufficient organic production experience [50], poor profitability [65], and market barriers [66], determine whether they continue to engage in OF based on their perception and confidence in their ability to overcome these difficulties, which affect the maintenance of adoption intentions by PBC. Certified farmers, with a higher level of knowledge and richer practical experience in OF, are less influenced by social norms. They are mainly concerned about the consequences of adopting OF, with attitude being the determining factor of adoption intention.

The data analysis in this study reveals that intention is the strongest driving factor for behavior, and favorable intention is a reliable antecedent to behavior [19]. Furthermore, Sriwichailamphan [9] found that farmers with larger farmland are more likely to adopt OF. We also found that farm size has a positive impact on adoption behavior. This may be due to the higher fixed costs associated with OF [34], which can be a heavier burden on small-scale farms. On the other hand, large-scale farms can leverage economies of scale to mitigate the adverse effects of fixed costs and gradually transition to OF, which can reduce uncertainty risks associated with changing production methods. Therefore, farmers with larger farm sizes are more likely to adopt OF. The finding that farm size has an impact on behavior beyond intention not only indicates a gap between intention and behavior, but also suggests that predicting behavior cannot solely rely on intention. Multi-group analysis reveals significant differences in the relationship between conventional farmers and conversion farmers in the FS→BEH. This may be attributed to the fact that larger farms entail higher costs and greater risks for conversion farmers, especially those facing difficulties, as the potential losses they may incur could lead them to abandon OF.

Finally, we found that, regardless of the group, attitude positively influences intention, and intention positively influences behavior. Cakirli Akyüz and Theuvsen [19] also made similar findings in their study. This suggests that there is a clear causal chain in the adoption of organic farming behavior: attitude → intention → behavior.

6. Conclusions

This study, guided by the TPB, utilizes PLS-SEM to explore the driving factors behind farmers' adoption of OF. We find that attitude, perceived behavioral control, subjective norms, and descriptive norms have positive impacts on intention, but the strength of the impact of subjective norms on intention differs between conventional farmers and conversion farmers. Intention and farm size positively drive behavior, but the impact of farm size on behavior varies between conventional farmers and conversion farmers. Most importantly, we discover an "attitude → intention → behavior" driving chain in the adoption decision-making process for conventional, conversion, and certified farmers. This study also demonstrates the applicability of TPB in studying the adoption of OF and its potential extension to similar high-cost pro-environmental behaviors.

The research results have important implications for the promotion of organic farming. It is evident that intention and evaluation of the consequences of adopting OF is a key driving factor for farmers' intentions to adopt OF. Promoters should take effective measures to stimulate farmers to form or maintain a positive evaluation of adopting OF. The most important measure may be the implementation of public payments, which includes providing certification subsidies, facilitating unified procurement of inputs, supporting research and development of efficient and low-input technologies, and constructing organic product marketing platforms in order to ensure farmers' financial income, which is their primary concern. Secondly, the organic sector should pay attention to the impact of driving factors on the adoption intentions of OF among different categories of farmers, and implement differentiated support policies to improve policy effectiveness. For example, guiding conventional farmers to adopt OF can leverage social public opinion favoring organic agriculture promotion and the radiating effect of demonstration bases. For conversion farmers, it is necessary to strengthen organic technology training and information services to help them solve organic technology challenges and increase yields. For certified farmers, assisting them in solving sales problems may be a key focus. Thirdly, the organic sector should support small farmers in building cooperative organizations to save production and transaction costs, obtaining economies of scale.

Although the model proposed in this paper is developed on a solid theoretical background, like any research, it also has limitations. Firstly, the conclusions drawn from the study sample, consisting of farmers mainly engaged in tea and fruit cultivation in four counties of Xiangxi Tujia and Miao Autonomous Prefecture, may not necessarily apply to other regions or contexts involved in the production of other agricultural products. Further research can expand the study area and organic product range. For example, selecting different agricultural production areas in Northeast or Western China as research areas could provide more general conclusions. Secondly, although the research model has strong predictive power for the adoption of organic farming behavior, there may be other influencing factors that have not been addressed, such as socio-demographic characteristics like risk preferences, which present opportunities for further research. Finally, the discussion of the driving factors behind farmers' adoption of organic farming behavior in this paper is based on quantitative analysis of sample data. Future research needs to consider adopting a case study method to analyze the causal process of the impact of driving factors on behavior.

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