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# A Study on Factors Influencing Farmers' Adoption of E-Commerce for Agricultural Products: A Case Study of Wuchang City

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**Abstract:** The widespread popularization of Internet technology has facilitated the emergence of e-commerce as a novel avenue for agricultural product sales, driven by its convenience and broad reach. Nevertheless, in Wuchang City, a well-developed agricultural region in northeastern China, some farmers still exhibit low enthusiasm for participating in agricultural product e-commerce, with limited levels of engagement. To investigate the underlying causes, this study analyzes survey data from 301 farmers in Wuchang City and uses mean difference significance tests and Logistic and Tobit regression models to explore the factors influencing farmers' adoption of e-commerce for agricultural products. The results demonstrate that gender and the number of household members involved in agricultural labor significantly influence the adoption decision and the extent of adoption. There is a significant difference in the adoption of decisions among ages. Subjective willingness and policy perception positively and significantly influence the adoption decision. Risk perception significantly and negatively impacts the extent of adoption. Infrastructure exerts a significant and negative influence on the adoption decision but a significant and positive influence on the extent of adoption. Based on these findings, this study suggests localized reforms, enhanced e-commerce promotion, and differentiated training to boost farmers' adoption, promoting sustainable development of the agricultural e-commerce economy.

**Keywords:** e-commerce for agricultural products; adoption behavior; mean difference significance test; regression model; influencing factors



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## 1. Introduction

As information technology rapidly advances in the 21st century, traditional agricultural economies are undergoing a transformative shift. Agriculture has evolved from the small-scale peasant economy dominated by manual labor to an era of smart agriculture, driven by advanced technologies such as the Internet [1]. In China, the agricultural e-commerce sector has experienced explosive growth, continually fostering new industries and business models in rural areas. The advancement of e-commerce for agricultural products plays an important role in expanding sales channels, enhancing farmers' incomes, and enhancing the development of rural informatization and digitization. China has placed a significant emphasis on the advancement of rural e-commerce, as evidenced by the "No. 1 Central Document", which has consistently prioritized the promotion of rural e-commerce as a major strategic initiative for rural revitalization over the past decade from 2014 to 2024 [2]. A number of macro policies have been introduced to guide the integration of the digital economy into rural areas. These policies have resulted in notable achievements. As indicated by data from the National Bureau of Statistics of China, China's grain output reached a record high of 669.5 million tons. Simultaneously, the total rural e-commerce sales in China amounted to 2.49 trillion yuan in 2023, representing a year-on-year increase of 12.9%. Of this, agricultural product transactions accounted for 23.58%, or 587.03 billion yuan, reflecting a 12.5% growth compared to 2022. The surge in online retail of agricultural products highlights the positive momentum of rural digitalization, which has greatly enhanced agricultural production efficiency [3]. The COVID-19 pandemic further deepened the importance of rural e-commerce as a vital channel for both promoting the sale of agricultural products and facilitating the flow of industrial goods to rural areas [4,5]. However, enthusiasm among farmers to engage in rural e-commerce remains modest, and their involvement in agricultural e-commerce is still relatively low [6]. Some farmers engage in agricultural e-commerce in a perfunctory manner, and in some cases, their involvement is more nominal than substantive, indicating significant potential for further development in the agricultural product e-commerce industry. Therefore, a thorough analysis of the various driving and constraining factors influencing farmers' adoption and level of engagement in agricultural e-commerce is crucial for promoting the sustainable development of the agricultural economy and improving the level of agricultural modernization [7].

The development of rural digitalization is closely linked to the level of activity in agricultural e-commerce [3,8,9]. The operational models and behavioral logic of farmers have consistently attracted the attention of scholars [10]. There is growing debate on how to promote the adoption of agricultural digital technologies from multiple perspectives, including technological, social, and political dimensions [11]. By reviewing the literature, agricultural digital technologies can generally be categorized into two main areas: agricultural equipment and technology (such as agricultural IoT, precision farming, and smart agricultural equipment) and agricultural products e-commerce.

Several factors influence farmers' willingness to use agricultural equipment and smart farming technologies, including income [12,13], social policies [14], farm size [15], technological complexity, and performance expectations [16,17]. These elements shape farmers' adoption of digital agricultural technologies. Additionally, the commercial development of agriculture-related fields also plays a key role in the management and decision-making of digital technology applications [12]. The emergence of e-commerce platforms has made the market pricing and supply–demand dynamics of agricultural products more transparent [18]. As a new sales channel, e-commerce promotes the deep processing of agricultural products and directly increases farmers' incomes [19–21]. Large-scale farms, new-generation farmers, and other emerging agricultural entities represent key focus groups for pursuing commercialization in marketing [22,23] and are more receptive to new technologies and models compared to other entities. As early adopters of e-commerce, they have a significant impact on the adoption willingness of later participants [24]. Joining farmer cooperatives, engaging in digital finance [25], and attending technical training sessions can increase farmers' propensity to adopt various digital agricultural solutions [26]. However, limited digital literacy and inadequate rural infrastructure remain major obstacles to farmers adopting these technologies [27]. Therefore, direct or indirect public interventions may be necessary [28]. Policies that incentivize and support farmers [29,30] can steer them toward the adoption of digital technologies [31], which in turn fosters innovation in digital agriculture [15,32]. The existing literature provides a solid foundation for this study. However, most of these studies on the adoption behavior in the field of agricultural digital technology are broad and general, and there is a relative lack of research on the dynamics and complexity of adoption behavior, especially in the developed agricultural regions of Northeast China.

Different countries and regions possess distinctive economic, political, and cultural backgrounds, and the factors influencing technology adoption will also change accordingly [33]. In order to further explore farmers' adoption behavior, the factors influencing their decisions, and the extent of agricultural products e-commerce adoption, this study selects farmers from Wuchang City, Heilongjiang Province, as the research objects. Heilongjiang, China's largest grain-producing province, boasts abundant agricultural resources. Wuchang is a typical large agricultural city within the province and was one of the first cities in China designated as a comprehensive rural e-commerce demonstration area. Wuchang's signature agricultural product, Wuchang rice, is renowned nationwide, serving as the city's leading industry and a major source of income for local farmers. In 2023, Wuchang's rice planting area reached 2.511 million acres, and the city's e-commerce transaction volume exceeded 6 billion yuan, with a year-on-year growth of 31%. For several consecutive years, the transaction volume has exceeded 5 billion yuan, with rural online sales amounting to 810 million yuan, up 35% year-on-year. Despite the development of e-commerce in the region over the past few years, there are still several challenges facing rice e-commerce in Wuchang, such as a shortage of e-commerce talent and low digital literacy among farmers These issues have hindered farmers' adoption of agricultural e-commerce. Based on the above analysis, this study mainly discusses and analyzes the following three issues: qualitative analysis and classification of farmers' adoption behavior; factors influencing farmers' adoption behavior; the reasons for the differences in influencing factors between farmers in the study area and farmers in other areas.

This study conducted a qualitative analysis of the extent of adoption and a theoretical analysis of influencing factors before creating a survey questionnaire. A survey was conducted in 2023, targeting 325 farmers from seven towns in Wuchang City, and the data were subjected to empirical analysis. Before starting the data analysis, this article evaluated the reliability and validity of the model, as well as the internal correlation of the variables. This study employed methods combining mean difference significance tests with Logistic and Tobit regression models to investigate how personal characteristics, household characteristics, and other factors in the Wuchang region influence farmers' adoption decisions and the extent of their adoption. This paper concludes with a discussion of this study's limitations and provides policy recommendations to further encourage farmers' adoption of e-commerce for agricultural products. The findings and policy suggestions presented in this research also hold forward-looking significance for other agricultural counties and cities in China's northeastern region.

## 2. Concept Definition and Theoretical Analysis

As the primary agents of agricultural production, farmers are profoundly shaped by a complex interplay of historical, cultural, economic, social, and political factors, which in turn influence their lifestyles, behavioral patterns, and decision-making processes. As a consequence of the rapid modernization of China, the traditional small-scale farming economy has undergone a rapid transition into a market economy, which has significantly enhanced the comprehensive capacity of the agricultural industry [34,35]. The behavior patterns of farmers have undergone unprecedented changes, as they increasingly embrace Internet technologies, utilizing e-commerce platforms to expand sales channels and improve the market competitiveness of their agricultural products. Since farmers' survival strategies and values evolve with changes in socio-economic conditions [10], the factors influencing their participation in e-commerce have become increasingly complex. To study farmers' adoption behavior, this research defines the concept of farmers' adoption of e-commerce for agricultural products by drawing from and organizing the existing literature (as shown in Table 1). The factors influencing farmers' adoption of e-commerce in this article can be grouped into the following categories: personal characteristics, household characteristics, subjective willingness, risk perception, infrastructure, industrial foundation, and policy perception. The classification of adoption behavior and the influencing factors on farmers' adoption of e-commerce for agricultural products are shown in Figure 1.

**Table 1.** Supporting references for factors influencing agricultural digital technology adoption.

| Literature | Research Object | A | B | C | D | E | F | G | H | I |
|---|---|---|---|---|---|---|---|---|---|---|
| [9] | Wisconsin farm | | Y | Y | Y | Y | Y | Y | Y | |
| [12] | Brazilian farmer | | Y | Y | Y | Y | Y | Y | | |
| [15] | Farmer in Shandong and Liaoning | | Y | Y | Y | | | | Y | Y |
| [16] | Farmers in small-scale area | Y | Y | Y | | | Y | | Y | Y |
| [17] | Italian farmer | Y | | Y | | Y | | | | Y |

**Table 1.** *Cont.*

| Literature | Research Object | A | B | C | D | E | F | G | H | I |
|---|---|---|---|---|---|---|---|---|---|---|
| [23] | Pakistani farmer | Y | | Y | Y | | Y | | | |
| [25] | Chinese farmer | Y | | Y | Y | | Y | Y | | |
| [26] | Ghana's small-scale farmer | Y | Y | Y | Y | | | | | Y |
| [28] | EU farmer | Y | | Y | | Y | | | | Y |
| [29] | Cross-regional farmer in European | Y | | Y | Y | Y | | | | |
| [36] | Chinese farmer | Y | | Y | Y | Y | | | | |
| [37] | Small-scale farmer | Y | | Y | Y | | | Y | Y | Y |
| [38] | Swiss farmer | Y | Y | Y | Y | | | | | |
| [39] | Sichuan small-scale farmer | Y | | Y | Y | | | Y | | |
| [40] | Shaanxi farmer | Y | | Y | | Y | | | | Y |
| [41] | British farmer | Y | | Y | Y | Y | | | | Y |
| [42] | Farmers from five countries | Y | | Y | Y | | | | | Y |

The variables in the header are replaced with numbers A to I. A represents the adoption decision; B represents extent of adoption; C represents personal factor; D represents household factor; E represents subjective willingness; F represents risk perception; G represents infrastructure; H represents the industrial foundation; I represents policy factors. The Y in the table represents studies related to this variable that appear in the literature.

1. The behavior of farmers adopting agricultural products e-commerce

Adoption behavior is a progressive, multi-level dynamic system that encompasses various stages, including initial cognitive formation, decision-making considerations, and the depth and breadth of technology application [43]. Measuring adoption behavior solely by whether or not adoption occurs, or by the intensity of adoption, fails to fully and accurately reflect its complexity and diversity.

The study of technology adoption behavior displays cross-disciplinary and multi-dimensional characteristics. A substantial number of scholars have made contributions to this field of study. For example, Frank et al. investigated the influence of innovation on various levels of technology adoption [44], Amjad et al. examined consumer e-commerce adoption behavior [45], Hook et al. analyzed national technology adoption rates [46], and Ronald et al. explored technology adoption decisions among the elderly [47]. These studies collectively demonstrate the diversity and variability in adoption behavior and adoption rates across different fields.

As a distinct social group, farmers are significantly affected by temporal and spatial shifts in their behavior [48]. In the field of sustainable agricultural development, it is essential to conduct research on farmers' adoption behavior. For example, Andrea et al. categorized digital technology adoption into four sequential stages, including entry-level technology, currently used technology, and planned short- and medium-term investments [16]. Licarion et al. examined the factors influencing the adoption of digital agricultural technology by analyzing the uptake of different digital agricultural solutions [26]. In a related study, Wei et al. examined the factors influencing farmers' adoption decisions when cooperating with e-commerce companies [40]. Yan et al. employed the proportion of apples sold via agricultural e-commerce to total production as an indicator of the extent of adoption [14].

This study focuses on farmers' adoption behavior regarding agricultural product e-commerce, which can be divided into two phases: the adoption decision and extent of adoption. The term "adoption decision" refers to the decision of a farmer to engage in and adopt e-commerce for agricultural products. The term "extent of adoption" is indicative of the level of involvement a farmer has in e-commerce. However, quantifying the extent of adoption can be challenging. Using the ratio of farmers' sales through e-commerce to total agricultural sales as a quantitative standard does not fully reflect the adoption level [49]. Therefore, this study categorizes the extent of adoption into two tiers: low adoption level and high adoption level. Low adoption level indicates that farmers only supply products to e-commerce platforms with limited participation, primarily serving as suppliers without deeper involvement in the operation and management of the e-commerce platform. In contrast, the high adoption level signifies that farmers actively engage in collaborative operations within agricultural e-commerce. This level of adoption involves deeper and broader participation, where farmers not only provide products but may also contribute to building brand identity, developing marketing strategies, managing customer information, and distributing profits.

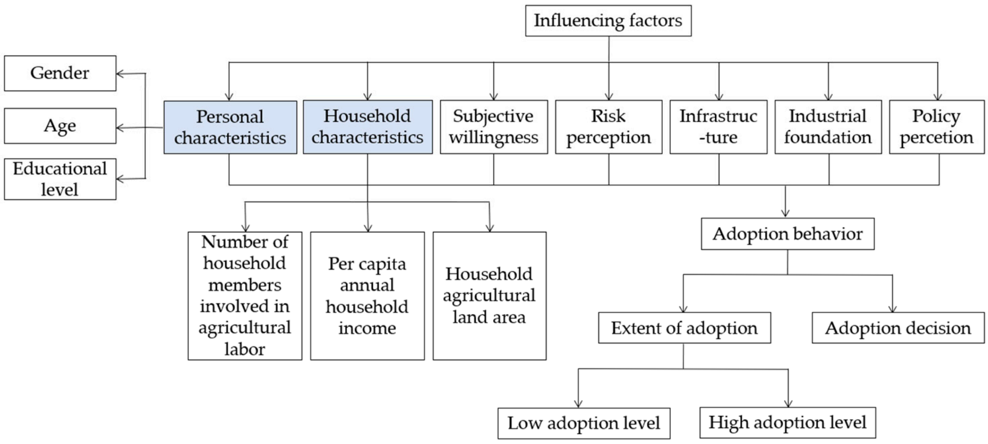


**Figure 1.** Classification of adoption behavior and its influencing factors.

2. Personal Characteristics

Personal characteristics are an integral part of the study of individual behavior. Individual differences in gender, age, and educational level can affect the way individuals make decisions and behave. The personal characteristics of farmers include three factors: gender, age, and educational level.

- Gender: The gender of a farmer may influence their cognition of the market, risk preferences, and attitude toward emerging industries [50]. Gender differences can influence individual acceptance and willingness to adopt digital technologies in agriculture [51]. Societal role expectations for males and females also influence their behavior in agricultural digital technology adoption. Men tend to communicate with the goal of constructing and maintaining social status or based on a personal internal drive, whereas, in contrast, women are more likely to communicate with the main goal of building harmonious relationships and following social norms and inclusiveness [52]. Therefore, it is hypothesized that gender has an impact on the adoption of e-commerce for agricultural products.
- Age: It is necessary to conduct research on different age groups. Elmira and Xin found that different age groups were influenced to different degrees when studying individual behavior [53,54]. Gao et al. found that younger farmers were more familiar with the Internet and e-commerce compared to older farmers [55], so it was hypothesized that the younger the age, the easier it is to adopt e-commerce for agricultural products.
- Educational level: The educational level reflects a farmer's knowledge reserve and learning ability. Gao et al. considered that education has a positive impact on farmers' willingness to adopt live-streaming e-commerce [55]. Farmers with higher educational levels may find it easier to understand and utilize e-commerce platforms [56,57]. Hence, it is hypothesized that the higher the educational level, the more likely a farmer is to adopt agricultural products through e-commerce.

3. Household characteristics

Household characteristics have a profound impact on behavior, making an understanding of these characteristics an indispensable part of personal behavior research. Knowledge of household characteristics helps to more accurately predict and explain individual behavior, thereby reducing bias and misunderstanding in the interpretation of behavior. The household characteristics of farmers include three factors: the number of household members involved in agricultural labor, per capita annual household income, and household agricultural land area.

- Number of household members involved in agricultural labor: The labor force is one of the key determinants of adoption strategies. The labor force is a critical factor in agricultural production, particularly regarding family labor and household members [58]. This factor may affect how time and resources are allocated within the household [59]. It is postulated that the number of household members involved in agricultural labor exerts an influence on the adoption of e-commerce for agricultural products.
- Per capita annual household income: Per capita annual income is the economic situation of the household. Households with higher per capita annual incomes may be more inclined to invest resources in the expansion of sales channels [50]. Gao et al. indicate that financial status has a significant positive impact on the intensity of adopting agricultural digital technologies [60]. It is therefore hypothesized that a higher per capita annual income will result in a greater likelihood of a household adopting e-commerce for agricultural products.
- Household agricultural land area: The area of cultivated land affects agricultural output [61]. A larger farm size generally correlates with increased production. Consequently, management becomes more complex, potentially necessitating greater resource investment in digital technologies and effective sales and market expansion strategies [17,57]. Thus, it is hypothesized that the larger the agricultural land area, the more likely a household is to adopt e-commerce for agricultural products.

4. Subjective Willingness

Subjective willingness can be defined as the intrinsic motivation, needs, and desires of farmers to participate in, utilize, or adopt e-commerce for agricultural products. It is a key variable in measuring farmers' enthusiasm for grain production [62]. The more positive the subjective willingness, the more likely individuals are to adopt a favorable attitude, leading to more proactive and effective adoption of technology [63–65]. Therefore, it is hypothesized that the more positive a farmer's attitude towards e-commerce for agricultural products, the more likely they are to adopt it.

5. Risk Perception

Risk perception refers to farmers' subjective understanding of the specific risks associated with adopting e-commerce for agricultural products [66]. In making decisions, individuals typically assess potential risks and adjust their attitudes and behaviors in accordance with their risk perception. Risk perception has a significant impact on people's behavior [67,68]. Risk attitude is the main driving factor for farmers' behavior. Perceived risks can have negative impacts, and individuals should feel comfortable interacting with technology to increase adoption rates [69]. The degree of risk perception among farmers directly influences their attitude toward and willingness to adopt e-commerce. Therefore, it is hypothesized that if farmers perceive potential risks associated with e-commerce to be high [70], they may exhibit a cautious and hesitant attitude towards its adoption.

6. Infrastructure

Infrastructure refers to the farmers' perception and evaluation of the requisite infrastructure for the adoption of e-commerce for agricultural products. Infrastructure can greatly improve individual satisfaction levels while stimulating and increasing adoption rates [71,72]. If farmers perceive poor infrastructure, it will constrain their adoption of precision and digital agricultural technologies [14,73]. If farmers perceive the level of infrastructure development to be high, it implies that they can more easily utilize e-commerce platforms for transactions [63,74]. Therefore, it is hypothesized that infrastructure has a positive impact on farmers' adoption of e-commerce for agricultural products.

7. Industrial foundation

The industrial foundation refers to farmers' perception and evaluation of the ability of the rural industry to meet the demands of e-commerce for agricultural products. If farmers perceive that the current scale and quality of agricultural production are sufficient to meet the requirements of e-commerce [74,75], they are more likely to adopt e-commerce for agricultural products.

8. Policy perception

Policy perception refers to the degree to which individuals or organizations comprehend and recognize government policies and regulations [43]. Individuals will evaluate things through perception, organization, interpretation, and other means, and their opinions will influence their decisions [76]. Those with a higher level of policy perception are more likely to evaluate the supportive role of external systems and environments in a positive manner [77]. Therefore, it is hypothesized that farmers' perception of government policies related to agricultural e-commerce directly influences their attitude towards and decision to adopt e-commerce.

## 3. Research Design

### *3.1. Research Area and Data Sources*

#### 3.1.1. Research Area

Wuchang City, located in the world's Golden Rice Belt at 45 degrees north latitude, benefits from geographic and climatic conditions that create an ideal environment for rice cultivation. The city's natural advantages have contributed to the superior quality of its rice. Local farmers rely on leading agricultural enterprises, rice-growing cooperatives, and family farms, which play a key role in driving the expansion of rice farming, making it the main source of income for farmers in the area. Wuchang City focuses on the specialized cultivation of a single crop—rice—which has created a distinct regional characteristic and established the superior brand influence of Wuchang rice.

In 2023, Wuchang's GDP reached 28.57 billion yuan, maintaining its position as the leading county-level economy in Heilongjiang Province, accounting for 4.5% of the province's total GDP. The agricultural products e-commerce industry has made a significant contribution to this achievement. In 2020, Wuchang ranked first among the top 10 counties promoting rural e-commerce in China, receiving recognition from the State Council. In 2021, it ranked tenth among the top 100 agricultural products e-commerce counties in China. By 2024, Wuchang's e-commerce revenue exceeded 5 billion yuan for five consecutive years, while the brand value of Wuchang rice surged to 71.31 billion yuan, making it the leading geographical product in the rice category for eight consecutive years. Currently, rural e-commerce in Wuchang covers 85% of the villages, with 224 village-level e-commerce service stations and 405 agent points in various villages. These figures mark the near completion of Wuchang's rural e-commerce system, providing solid support for the upward movement of agricultural products.

The Wuchang government has attached great importance to the development of agricultural products e-commerce in the region and has established several agricultural e-commerce logistics parks. It has also implemented "the Wuchang Rice Industry Development Action Plan and Vision for 2024–2026" while promoting the growth of the e-commerce sector through policy support, financial subsidies, and free e-commerce skills training.

#### 3.1.2. Data Sources

To ensure the representativeness and reliability of the sample data, this study selected seven townships within the core production area of Wuchang rice in Wuchang City, including Longfengshan Township, Changshan Township, Wuchang Town, Dujia Town, Minyi Township, Xiaoshanzi Town, and Weiguo Township, as the survey scope. These areas essentially cover the core rice-producing regions of Wuchang City, with their specific locations shown in Figure 2. Using a random sampling method based on population size, three villages were randomly selected from each township, and 15 to 30 households were randomly selected from each village. The sample households had to be those actually involved in rice farming or rice cultivation.

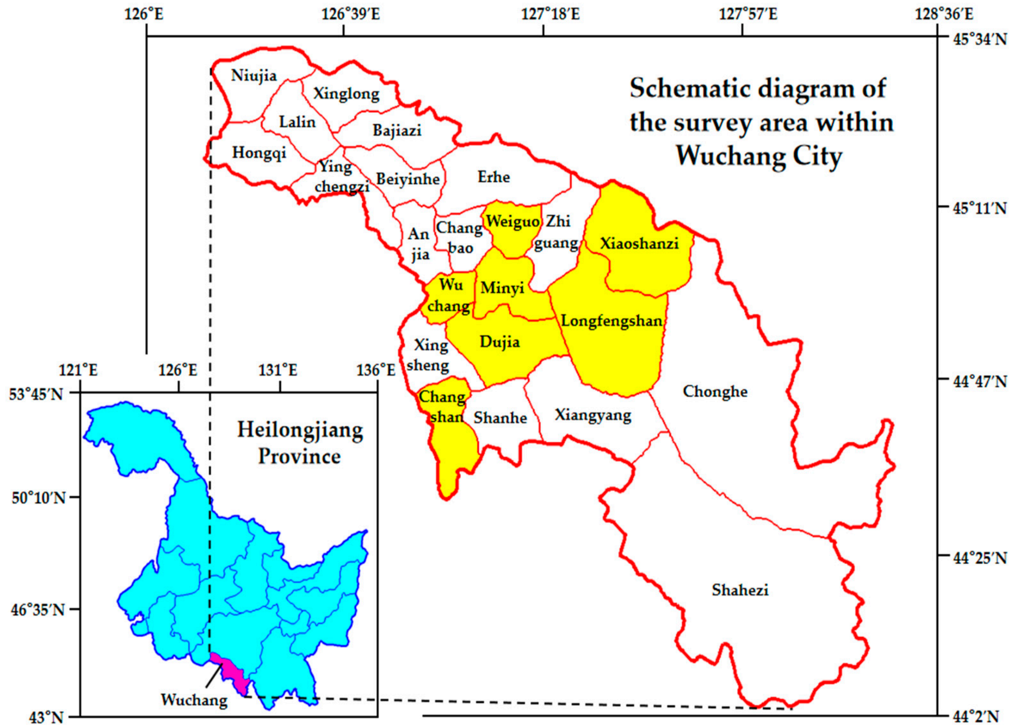


**Figure 2.** Schematic diagram of Wuchang City and survey area within Heilongjiang Province.

Field research and data collection through questionnaires were conducted in Wuchang City, Heilongjiang Province, from January to February 2023. The survey data were collected using a structured questionnaire, which consisted of two parts: The first part covered the basic information of the households, and the second part included questions related to factors influencing the adoption of agricultural e-commerce by the farmers.

Prior to the formal survey, a pilot study involving 50 farmers from Wuchang City was conducted. The questionnaire was revised based on the feedback, and unclear questions were removed. After revising the questionnaire, a formal survey was conducted with 325 households. Given that some farmers had lower educational levels and limited comprehension abilities, part of the data was collected through offline household interviews and in-person Q&A sessions to improve data accuracy, while the remaining farmers completed the survey through online questionnaires. Additionally, respondents were informed that participation was voluntary. As compensation for their time and effort, a cash incentive was provided upon completing the interviews and questionnaires. A total of 325 responses were collected, and after filtering out incomplete and abnormal data, 301 valid questionnaires were obtained, resulting in an effective response rate of 92.6%.

### *3.2. Variable Definition*

In this study, the farmers' adoption decision and the extent of adoption are treated as dependent variables. For the adoption decision, samples where farmers have not adopted e-commerce for agricultural products are assigned a value of 0, while samples where farmers have adopted e-commerce are assigned a value of 1. For the extent of adoption, samples with low adoption (where farmers only supply agricultural products to operators) are assigned a value of 0, while samples with high adoption (where farmers participate in cooperative management of e-commerce) are assigned a value of 1.

The personal characteristics, household characteristics, subjective willingness, risk perception, infrastructure, industrial foundation, and policy perception of the surveyed farmers are assigned values using a Likert five-point scale, with values ranging from "Strongly Disagree" to "Strongly Agree" represented by "1" to "5", respectively. The specific measurement indicators are shown in Table 2.

**Table 2.** Specific measurement indicators for the farmers' adoption of e-commerce.

| Dimensions | Measurement Indicators |
| --- | --- |
| **Adoption behavior** | Adoption decision<br>Extent of adoption |
| **Subjective willingness** | I am willing to learn skills related to agricultural products e-commerce.<br>I am willing to participate in training related to agricultural products e-commerce. |
| **Risk perception** | I think there is a high risk of default for agricultural products e-commerce orders.<br>I think after-sales and reputation issues have a significant impact on the operation of agricultural product e-commerce. |
| **Infrastructure** | The road construction in my area is well-developed.<br>The broadband network infrastructure in my area is well-developed. |
| **Industrial foundation** | The current scale of agricultural production can support the demand for e-commerce of agricultural products.<br>The quality of agricultural products can meet the demand for agricultural products e-commerce. |
| **Policy perception** | I think government policies are effective.<br>I think the policy support is strong. |

### *3.3. Regression Model*

In the study of adoption behavior, scholars often use methods such as multivariate logistic models, econometric models, structural equation models, and probit models [23,40,41,47,78]. To investigate the impact of farmers' cognitive behavior and environment on their participation in adopting agricultural product e-commerce behavior, this paper uses logistic regression combined with Tobit regression model to explore it.

The decision of farmers to adopt agricultural products e-commerce is a binary variable, and using a Logistic regression model can better overcome the requirement for variable continuity. Assuming the response probability of farmers' decision to adopt agricultural products e-commerce is $P$, the corresponding Logistic regression model is shown in Equation (1):

$$Y_1 = In\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_i x_i + \cdots + \beta_m x_m + \varepsilon \quad (1)$$

In Equation (1), $Y_1$ represents the dependent variable of farmers' adoption decision; $\beta_0$ represents the regression intercept; $\varepsilon$ is the random disturbance term; $x_i$ represents the dependent variable; $\beta_i$ is the regression coefficient of the corresponding dependent variable, which can be obtained through maximum likelihood estimation.

Because the dependent variable $Y_2$ represents the extent of adoption based on the farmers' decision to adopt, and there is a truncation phenomenon in the value, it is a restricted dependent variable. Therefore, the Tobit regression model is used, as shown in Equation (2):

$$Y_i^* = \alpha + \sum \beta_i x_i + \mu_i Y_2 = \begin{cases} Y_i^*,\ if\ Y_i^* > 0 \\ 0,\ if\ Y_i^* \leq 0 \end{cases} \quad (2)$$

In Equation (2), $Y_i^*$ is the latent variable; $Y_2$ is the observed dependent variable; $x_i$ is the independent variable; $\beta_i$ is the correlation coefficient; $\alpha$ is a constant term; $\mu_i$ is the random error term.

## 4. Result Analysis Discussion

### *4.1. Reliability and Validity Testing*

The reliability and validity of a survey questionnaire are critical indicators for evaluating its quality [79]. Before conducting quantitative analysis, this study assessed the reliability and validity of all the items in the questionnaire. Reliability refers to the consistency, stability, and dependability of the measurement results, indicating how trustworthy the data from the questionnaire are. The Cronbach's Alpha coefficient is the standard used to assess reliability, with values ranging from 0 to 1, where a higher number indicates better reliability. The Cronbach's Alpha coefficient in this study was 0.729, which falls within the acceptable range of 0.8 to 0.9, suggesting that the measurement of variables demonstrates good reliability.

Validity refers to the degree to which a measurement tool or method accurately assesses the intended concept, reflecting the effectiveness of the research findings. The Kaiser–Meyer–Olkin (KMO) value and Bartlett's test of sphericity are fundamental indicators used to evaluate validity. In this study, the KMO value was 0.768, which falls within the range of 0.7 to 0.8, indicating good validity. Additionally, Bartlett's test of sphericity showed a significance level of 0.000, which is less than 0.05, indicating a highly significant result. This demonstrates that the questionnaire items align well with the research content, and the validity is robust.

Overall, our survey questionnaire exhibits strong reliability and validity.

### 4.2. Collinearity Test

Since internal correlations may exist between variables, ensuring the model design and estimation results are reasonable and effective requires testing for multicollinearity. One commonly used indicator for this is the Variance Inflation Factor (VIF). Generally, when the VIF is close to 1, it indicates that multicollinearity between the independent variable and other variables is weak or non-existent. If the VIF is between 1 and 5, multicollinearity is considered within an acceptable range, and while some collinearity may exist, it typically does not significantly affect model estimation. However, when the VIF exceeds 5, it suggests a certain degree of multicollinearity between the variables.

The results of the multicollinearity test conducted in this study are presented in Table 3. The maximum VIF value observed was 2.014, indicating that there is no severe multicollinearity problem among the explanatory variables.

**Table 3.** Results of multicollinearity test.

| Variable | Adoption Decision | | Extent of Adoption | |
|---|---|---|---|---|
| | Tolerance | VIF | Tolerance | VIF |
| **Gender** | 0.976 | 1.025 | 0.947 | 1.056 |
| **Age** | 0.595 | 1.68 | 0.496 | 2.014 |
| **Educational level** | 0.597 | 1.676 | 0.519 | 1.927 |
| **Number of household members involved in agricultural labor** | 0.929 | 1.077 | 0.911 | 1.098 |
| **Per capita annual household income** | 0.931 | 1.074 | 0.908 | 1.101 |
| **Household agricultural land area** | 0.949 | 1.054 | 0.918 | 1.089 |
| **Subjective willingness** | 0.766 | 1.306 | 0.847 | 1.18 |
| **Risk perception** | 0.776 | 1.289 | 0.788 | 1.269 |
| **Infrastructure** | 0.731 | 1.368 | 0.724 | 1.38 |
| **Industrial foundation** | 0.754 | 1.326 | 0.834 | 1.199 |
| **Policy perception** | 0.759 | 1.318 | 0.793 | 1.261 |

### 4.3. Descriptive Statistical Analysis

The descriptive statistics in Table 4 indicate that 199 out of the sampled farmers have adopted e-commerce for agricultural products, accounting for 66.1% of the total sample. Among the households that adopted e-commerce, 51.3% had a low level of adoption, while 48.7% exhibited a high level of adoption. This shows that there are more households with a low level of adoption compared to those with a high level. The gender distribution among the sampled farmers is 55.8% male and 44.2% female. Farmers aged 45–60 represent 55.8% of the sample, which is higher compared to other age groups. Among the sampled farmers, 43.2% have an education level ranging from primary to junior high school. The proportion of farmers with a household agricultural land area exceeding 60 acres is relatively small, at 17.3%. The distributions of per capita annual household income and number of laborers are relatively balanced across different groups.

**Table 4.** Variable definition and descriptive statistics.

| Variable | | Project and Value Assignment | People | Proportion% |
|---|---|---|---|---|
| **Adoption behavior** | **Adoption decision** | No adoption = 0 | 102 | 33.9 |
| | | Adoption = 1 | 199 | 66.1 |
| | **Extent of adoption** | Low adoption level = 0 | 102 | 51.3 |
| | | High adoption level = 1 | 97 | 48.7 |
| **Personal characteristics** | **Gender** | Male = 0 | 168 | 55.8 |
| | | Female = 1 | 133 | 44.2 |
| | **Age** | ≤30 = 1 | 33 | 11 |
| | | 31–45 = 2 | 56 | 18.6 |
| | | 45–60 = 3 | 157 | 52.2 |
| | | ≥60 = 4 | 55 | 18.3 |
| | **Educational level** | No educational background = 1 | 51 | 16.9 |
| | | Primary or junior high school education = 2 | 130 | 43.2 |
| | | Senior school or technical secondary school education = 3 | 81 | 23.6 |
| | | College degree or above = 4 | 49 | 16.3 |
| **Household characteristics** | **Number of household members involved in agricultural labor** | 1 = 1 | 64 | 21.3 |
| | | 2 = 2 | 98 | 32.6 |
| | | 3 = 3 | 78 | 25.9 |
| | | ≥4 = 4 | 61 | 20.3 |
| | **Per capita annual household income** | ≤10,000 RMB = 1 | 68 | 22.6 |
| | | 10,000–20,000 RMB = 2 | 70 | 23.3 |
| | | 20,000–30,000 RMB = 3 | 69 | 22.9 |
| | | ≥30,000 RMB = 4 | 94 | 31.2 |
| | **Household agricultural land area** | ≤20 acres = 1 | 91 | 30.2 |
| | | 20–40 acres = 2 | 87 | 28.9 |
| | | 40–60 acres = 3 | 71 | 23.6 |
| | | ≥60 acres = 4 | 52 | 17.3 |

### *4.4. Analysis of the Influence of Farmers' Characteristics on E-Commerce Participation Behavior*

To ascertain the impact of farmers' demographic characteristics on their adoption behavior of e-commerce for agricultural products, we conducted a mean difference significance test. Specifically, gender was employed as the independent variable in an independent samples *t*-test, while age and educational level were subjected to one-way ANOVA (Analysis of Variance). The results are presented in Tables 5–7. The one-way ANOVA was employed to analyze the household characteristics, including the number of household members involved in agricultural labor, per capita annual household income, and household agricultural land area. The results are presented in Tables 8–10.

**Table 5.** Independent samples *t*-test of gender.

| Variable | Assignment | Mean | Standard Deviation | *t* | *p* |
|---|---|---|---|---|---|
| **Adoption decision** | 0 | 0.589 | 0.493 | −3.039 | 0.003 ** |
| | 1 | 0.752 | 0.434 | | |
| **Extent of adoption** | 0 | 0.374 | 0.486 | −3.261 | 0.001 *** |
| | 1 | 0.600 | 0.492 | | |

Note: **, *** respectively indicate statistically significant coefficient estimates at the 5%, and 1% levels (the same applies below).

**Table 6.** One-way ANOVA of age.

| Variable | Assignment | Mean | Standard Deviation | F | p |
|---|---|---|---|---|---|
| **Adoption decision** | 1 | 0.697 | 0.467 | 3.045 | 0.029 ** |
| | 2 | 0.732 | 0.447 | | |
| | 3 | 0.586 | 0.494 | | |
| | 4 | 0.782 | 0.417 | | |
| **Extent of adoption** | 1 | 0.522 | 0.511 | 1.086 | 0.356 |
| | 2 | 0.585 | 0.499 | | |
| | 3 | 0.424 | 0.497 | | |
| | 4 | 0.512 | 0.506 | | |

Note: ** respectively indicate statistically significant coefficient estimates at the 5% levels (the same applies below).

**Table 7.** One-way ANOVA of educational level.

| Variable | Assignment | Mean | Standard Deviation | F | p |
|---|---|---|---|---|---|
| **Adoption decision** | 1 | 0.726 | 0.451 | 1.065 | 0.364 |
| | 2 | 0.631 | 0.484 | | |
| | 3 | 0.620 | 0.489 | | |
| | 4 | 0.735 | 0.446 | | |
| **Extent of adoption** | 1 | 0.568 | 0.502 | 2.501 | 0.061 * |
| | 2 | 0.500 | 0.503 | | |
| | 3 | 0.318 | 0.471 | | |
| | 4 | 0.583 | 0.500 | | |

Note: * respectively indicate statistically significant coefficient estimates at the 10% levels (the same applies below).

**Table 8.** One-way ANOVA of number of household members involved in agricultural labor.

| Variable | Assignment | Mean | Standard Deviation | F | p |
|---|---|---|---|---|---|
| **Adoption decision** | 1 | 0.813 | 0.393 | 2.816 | 0.039 ** |
| | 2 | 0.622 | 0.487 | | |
| | 3 | 0.615 | 0.490 | | |
| | 4 | 0.623 | 0.489 | | |
| **Extent of adoption** | 1 | 0.327 | 0.474 | 2.774 | 0.043 ** |
| | 2 | 0.508 | 0.504 | | |
| | 3 | 0.542 | 0.504 | | |
| | 4 | 0.605 | 0.495 | | |

Note: ** respectively indicate statistically significant coefficient estimates at the 5% levels (the same applies below).

**Table 9.** One-way ANOVA of per capita annual household income.

| Variable | Assignment | Mean | Standard Deviation | F | p |
|---|---|---|---|---|---|
| **Adoption decision** | 1 | 0.618 | 0.49 | 1.199 | 0.31 |
| | 2 | 0.743 | 0.44 | | |
| | 3 | 0.681 | 0.469 | | |
| | 4 | 0.617 | 0.489 | | |
| **Extent of adoption** | 1 | 0.476 | 0.505 | 0.02 | 0.996 |
| | 2 | 0.500 | 0.505 | | |
| | 3 | 0.489 | 0.505 | | |
| | 4 | 0.483 | 0.504 | | |

The *p*-value for gender in relation to the adoption decision and the extent of adoption are 0.003 and 0.001, respectively, indicating that there are significant differences in the adoption of e-commerce for agricultural products based on gender. The results indicate that female farmers have higher means for both the adoption decision and the extent of adoption in comparison to male farmers, suggesting that women are more inclined to adopt e-commerce for agricultural products and have a higher level of adoption. The results are presented in Table 5.

**Table 10.** One-way ANOVA of household agricultural land area.

| Variable | Assignment | Mean | Standard Deviation | F | *p* |
|---|---|---|---|---|---|
| **Adoption decision** | 1 | 0.593 | 0.494 | 1.227 | 0.300 |
| | 2 | 0.701 | 0.460 | | |
| | 3 | 0.718 | 0.453 | | |
| | 4 | 0.635 | 0.486 | | |
| **Extent of adoption** | 1 | 0.5 | 0.505 | 2.135 | 0.097 |
| | 2 | 0.459 | 0.502 | | |
| | 3 | 0.608 | 0.493 | | |
| | 4 | 0.333 | 0.479 | | |

The *p*-value for age in relation to the adoption decision is 0.029, indicating a significant difference in adoption decision based on age. The data indicate that farmers aged 60 and above are comparatively more inclined to adopt e-commerce than other age groups. The results are presented in Table 6.

The *p*-value for the number of household members involved in agricultural labor in relation to the adoption decision and the extent of adoption are 0.039 and 0.043, respectively, showing significant differences in adoption behavior based on the number of laborers. Households with only one agricultural laborer have higher mean adoption values, suggesting that households with a single laborer are more inclined to adopt e-commerce. Additionally, the mean extent of adoption is observed to increase with the number of laborers, indicating that a higher number of laborers is associated with a greater degree of e-commerce adoption. The results are presented in Table 8.

There are no significant differences in adoption behavior based on educational level, per capita annual household income, or household agricultural land area. This indicates that while these three variables may have some facilitative or hindering effects, they are not decisive factors in the adoption of e-commerce for agricultural products. The results are presented in Tables 7, 9 and 10.

### *4.5. Analysis of Regression Model Estimation Results*

The results of the regression model estimation are summarized in Table 11. The *p*-value for gender, number of laborers, and infrastructure are all less than 0.05, indicating that these variables have a significant relationship with both the decision to adopt e-commerce for agricultural products and the extent of adoption.

Gender has a positive impact on the adoption behavior of e-commerce for agricultural products, with coefficients of 0.881 for the adoption decision and 0.222 for the extent of adoption. This suggests that gender has a stronger influence on the adoption decision than on the extent of adoption.

Number of household members involved in agricultural labor shows a negative impact on the adoption decision, with a coefficient of $-0.351$, but a positive relationship with the extent of adoption, with a coefficient of 0.081. This indicates that while a higher number of laborers is associated with a lower likelihood of adopting e-commerce, it is associated with a higher extent of adoption among those who do adopt.

Infrastructure has a negative impact on the adoption decision, with a coefficient of $-0.47$, but a positive relationship with the extent of adoption, with a coefficient of 0.112. This suggests that better infrastructure is linked to a lower likelihood of adoption but a higher extent of adoption among those who do adopt.

Subjective willingness is significantly related to the adoption decision, with a *p*-value of 0.042 and a positive coefficient of 0.433, indicating that a higher level of subjective willingness positively influences the decision to adopt e-commerce.

Risk perception significantly affects the extent of adoption, with a *p*-value of 0.048 and a negative coefficient of −0.105. This implies that greater risk perception is associated with a lower extent of adoption.

Policy perception significantly influences the adoption decision, with a *p*-value of 0.018 and a positive coefficient of 0.482, indicating that a more favorable perception of policies is associated with a higher likelihood of adopting e-commerce.

**Table 11.** Estimation results of regression model for farmers' adoption of e-commerce for agricultural products.

| Variable | Model 1 (Adoption Decision) | | | Model 2 (Extent of Adoption) | | |
|---|---|---|---|---|---|---|
| | Coefficient | Standard Deviation | *p* | Coefficient | Standard Deviation | *p* |
| **Gender** | 0.881 | 0.271 | 0.001 *** | 0.222 | 0.068 | 0.001 *** |
| **Age** | 0.025 | 0.192 | 0.897 | −0.054 | 0.052 | 0.291 |
| **Educational level** | −0.124 | 0.172 | 0.473 | −0.027 | 0.047 | 0.562 |
| **Number of household members involved in agricultural labor** | −0.351 | 0.130 | 0.007 ** | 0.081 | 0.033 | 0.013 ** |
| **Per capita annual household income** | −0.002 | 0.115 | 0.989 | −0.018 | 0.031 | 0.554 |
| **Household agricultural land area** | 0.196 | 0.123 | 0.110 | −0.027 | 0.033 | 0.408 |
| **Subjective willingness** | 0.433 | 0.213 | 0.042 ** | 0.029 | 0.053 | 0.586 |
| **Risk perception** | 0.026 | 0.197 | 0.894 | −0.105 | 0.053 | 0.048 ** |
| **Infrastructure** | −0.470 | 0.219 | 0.032 ** | 0.112 | 0.056 | 0.044 ** |
| **Industrial foundation** | −0.145 | 0.222 | 0.513 | −0.003 | 0.057 | 0.958 |
| **Policy perception** | 0.482 | 0.203 | 0.018 *** | −0.003 | 0.052 | 0.952 |
| **Constant** | −0.305 | 1.324 | 0.818 | 0.180 | 0.395 | 0.649 |
| **Log likelihood** | | −177.854 | | | −131.344 | |
| **Chi-square test** | | 29.74 *** | | | 27.83 *** | |
| **Pseudo R2** | | 0.077 | | | 0.090 | |

Note: **, *** respectively indicate statistically significant coefficient estimates at the 5%, and 1% levels (the same applies below).

## 5. Discussion of Results

Many scholars have found that the adoption of digital agricultural technology can enhance productivity and have income-boosting effects [80,81], with higher levels of adoption leading to higher incomes [9]. In less developed agricultural regions, e-commerce has significantly promoted entrepreneurship among farmers [70]. In more developed agricultural areas, leading agricultural enterprises, farmer cooperatives, and family farms often play an active role in driving other farmers to adopt e-commerce for agricultural products. According to the theory of social embeddedness, individuals tend to follow the majority and seek social recognition, which leads them to make similar decisions [82]. Under this influence, an increasing number of farmers are joining the e-commerce industry. However, some farmers have not yet adopted agricultural e-commerce, and in this study, around half of those who have adopted it demonstrate low levels of adoption, accounting for 51.3% of adopters, 2.6% more than those with a high level of adoption. Some scholars have pointed out that the farming community is highly heterogeneous, with many unobserved differences [83]. This study explores the reasons behind these inconsistencies from various influencing factors.

Gender has a significant impact on the adoption of agricultural e-commerce behavior in terms of personal characteristics, consistent with the speculation in this article. The specific results indicate that there is a difference in the influence of gender on the adoption of agricultural e-commerce by farmers, with the effect on adoption decisions being more pronounced than the extent of adoption. In contrast to the findings of this study, studies by Moslem et al. investigated farmers in southwestern Iran and Afghanistan and found that female farmers were less likely than male farmers to adopt modern technologies [84,85]. The possible reason is that the difference in the degree of development of regions will affect the proportion of Internet resources used by different genders. At the same time, religious beliefs and local customs and culture will affect the use of advanced technology and Internet resources. According to the data of the International Telecommunication Union, in underdeveloped countries, women's lack of livelihood opportunities, low literacy, lack of confidence in technology, conservative social norms, and other reasons have hindered women from owning and using Internet resources, leading to a gender digital divide that is still obvious. Su found that men use the Internet mainly through online games and other entertainment projects, while women use the Internet more through social media, so women will be exposed to more advertising, preferential information, product recommendations, and other information from the Internet [86]. Based on this, this article speculates that women tend to use the Internet more frequently and on social networks for a longer period of time and have a stronger demand for social networks and information acquisition. Therefore, compared to men, they are more likely to have access to information related to agricultural product e-commerce and are therefore more inclined to adopt agricultural product e-commerce. After adopting e-commerce for agricultural products, women are more active in social networks and customer communication and are more inclined to build long-term customer relationships through e-commerce and continuously improve services. This social interaction is crucial for deep participation in e-commerce. However, due to the relatively dominant position of men in agricultural production, they may use e-commerce as an auxiliary channel rather than as a main source of income and are therefore reluctant to invest too much energy and resources in e-commerce operations. Number of labor force has a significant impact on the adoption of e-commerce for agricultural products in terms of household characteristics, consistent with the hypothesis of this study. Specifically, the number of household members involved in agricultural production negatively affects the decision to adopt e-commerce but positively correlates with the extent of adoption. Labor has a significant positive impact on agricultural production [58]. The involvement of a greater number of family members in agricultural work results in a greater investment of time and effort in agricultural production, which in turn reduces the likelihood of adopting e-commerce. Nevertheless, as e-commerce is adopted, the extent of adoption gradually rises in tandem with an increase in the number of laborers. This is due to the fact that the household's primary source of income is derived from the production and sale of agricultural products, which provides an incentive for greater involvement in e-commerce with the aim of increasing revenue. Therefore, the government can design a series of tiered incentive measures to provide progressive support for families and encourage women to drive household members to participate in e-commerce operations. This would facilitate women's ascendance to an important role within the e-commerce business sector.

Infrastructure has a negative impact on the adoption decision but a positive correlation with the extent of adoption, which is inconsistent with the hypothesis of this study. The negative impact on the adoption decision may stem from its optimization effect on traditional agricultural product sales channels. As road and communication infrastructure improves, economies of scale will emerge in agricultural productivity and sales volume [38], farmers have more channels to sell agricultural products to the outside world, which in turn leads to a reduced willingness to adopt e-commerce. After farmers adopt agricultural product e-commerce, the infrastructure shows a positive impact, possibly due to enhanced road networks and communication methods that facilitate improved logistics efficiency and provide greater convenience for agricultural product sales. Consequently, they are more likely to engage extensively in agricultural product e-commerce. The difference in positive and negative impacts reflects the multiple effects of infrastructure, that is, during the adoption decision-making stage, infrastructure may reduce the necessity for farmers to choose e-commerce, but after adoption, it provides significant support for e-commerce operations. In light of the aforementioned analysis, it is recommended that the government consider providing subsidies for logistics and e-commerce training, among other measures, with the aim of facilitating the adoption of e-commerce by farmers and ensuring that they have access to high-quality and convenient services from the outset. This will help them overcome the initial challenges in the early stages of e-commerce.

Subjective willingness has a significant and positive impact on the decision to adopt agricultural products e-commerce, which aligns with the hypothesis of this study. Wei et al. considered that farmers' willingness has a positive influence on their participation in e-commerce activities [40]. The stronger the farmers' subjective willingness, the more positive their attitude. When farmers express a positive subjective willingness, it reflects an open attitude towards e-commerce, leading to a higher likelihood of adopting e-commerce. Risk perception has a significant and negative relationship with the level of adoption, which is consistent with the hypothesis of this study. Nawab et al. revealed in a survey of Pakistani farmers that risk awareness was unrelated to adoption behavior, which differs from the findings of this study [23]. The possible reason is that the levels of e-commerce development and risk awareness vary in different regions. Against the backdrop of the rapid development of e-commerce in China, the market competition faced by Chinese farmers has become more intense and demand has fluctuated greatly. Correspondingly, they have more exposure to e-commerce-related risk information and have a better understanding of the risks involved. Therefore, when farmers have concerns about the risks of agricultural e-commerce, the extent of their adoption tends to be lower. Policy perception has a significant and positive impact on the decision to adopt, which aligns with the hypothesis of this study. Gen et al. conducted surveys in Shandong and Jiangxi, China, and their findings are consistent with the results of this study [15,38]. However, Wei et al. discovered that government policies did not exert a direct, positive influence on adoption in a survey of farmers in Shaanxi [40]. The reason may be that different regions have different levels of economic development, e-commerce advancement, and government attention, which exert varying influences on farmers' perceptions of policies. The e-commerce industry is relatively well-developed in Wuchang City, and the government has implemented numerous policies to facilitate its growth. As a result, farmers in this region possess a more profound comprehension and perception of these policies. When farmers evince a favorable attitude toward e-commerce policies, they are more inclined to adopt agricultural e-commerce. In light of the aforementioned analysis, it is recommended that the government implement a pricing and transportation guarantee mechanism for agricultural product e-commerce through collaboration with enterprises. This would serve to safeguard the fundamental income of farmers from the detrimental effects of significant market price fluctuations, while simultaneously facilitating the reliable and punctual delivery of agricultural products to market. Concurrently, it is imperative to remain abreast of contemporary developments in policy and technology, furnish periodic technical assistance and policy interpretation, and mitigate the risks associated with a lack of familiarity with technological and policy updates. In formulating risk resistance policies related to agricultural e-commerce, the government should develop a range of information dissemination methods to promote policy benefits, particularly in the areas of pricing, logistics, insurance, and security. It is essential to enhance farmers' confidence in agricultural product e-commerce and reduce their risk expectations.

## 6. Limitations

This article categorizes the adoption behavior of farmers in Wuchang City into three scenarios: no adoption, low adoption level, and high adoption level, further dividing these into two categories: adoption decision and extent of adoption. Based on a summary of relevant studies on farmers' adoption of agricultural digital technology, the article critically examines the effects of personal characteristics, household characteristics, subjective willingness, risk perception, infrastructure, industrial foundation, and policy perception on adoption behavior. However, this article still has the following limitations:

1. Research sample limitations: This study focuses primarily on farmers in the rice-growing areas of Wuchang City. Although this choice highlights regional characteristics and represents the local agricultural context, it limits the generalizability of

the study's conclusions. As Wuchang is a well-known rice-growing area, farmers here may have unique agricultural practices, technology adoption levels, and market environments. Therefore, the results of this study may not be directly applicable to other crop-growing areas or regions with different economic environments. Future research should consider expanding the sample to include farmers from different crop types to improve the general applicability of the conclusions;

2. Insufficient classification of adoption level: The present study categorizes the extent of adoption of e-commerce for agriculture into two levels: low adoption and high adoption. While this classification is useful for analysis, it may fail to account for the nuanced differences and stages of farmers' e-commerce usage. Future research should develop more sophisticated measurement standards that integrate both qualitative and quantitative methods to more accurately capture the complexities of farmers' e-commerce adoption behavior across multiple dimensions.

## 7. Conclusions and Policy Recommendations

The purpose of this study is to qualitatively divide the extent of adoption and analyze the influencing factors of farmers' adoption of e-commerce for agricultural products in Wuchang City, thereby providing a scientific basis for enhancing farmers' willingness to participate in agricultural products e-commerce. This is of great significance in facilitating the rapid integration of farmers into the agricultural informatization process, thereby further promoting rural economic development.

This study employed a random sampling methodology to collect survey questionnaire data from farmers in the core rice-producing areas of Wuchang City. Using mean difference significance tests in combination with Logistic and Tobit regression models, this study analyzes the factors influencing farmers' adoption of e-commerce for agricultural products. This article draws the following conclusions:

1. The findings reveal that the factors affecting adoption decisions and the extent of adoption differ. The progression from making an adoption decision to a low adoption level and then high adoption level is a dynamic process in which the significance and importance of different factors change over time;
2. Gender, age, number of household members involved in agricultural labor, subjective willingness, infrastructure, industrial foundation, and policy perception show varying impacts on adoption decisions. Meanwhile, gender, educational level, number of household members involved in agricultural labor, risk perception, and infrastructure display differences in their influence on adoption levels.
3. Due to their unique economic, political, and social backgrounds, farmers in Wuchang City exhibit differences in their performance on different influencing factors compared to farmers in other regions.

Based on the previous discussion and analysis, this article proposes the following policy recommendations aimed at fostering the adoption of e-commerce for agricultural products among farmers:

1. The local governments should develop policies that are specifically tailored to the unique circumstances of farmers in their respective areas. It is essential that these policies explicitly prioritize the advancement of agricultural e-commerce. Tailored policy formulation will help better meet the needs of farmers in different regions.
2. Strengthen e-commerce promotion to ensure that farmers can understand agricultural product e-commerce from different channels of information acquisition so that the experience and advantages of agricultural product e-commerce can be widely and effectively disseminated and shared, thereby increasing farmers' trust in e-commerce.
3. The government should differentiate between different backgrounds and cover different levels of farmers, carry out differentiated training, ensure that farmers receive targeted assistance during the training process, and provide opportunities for farmers from different levels and regions to learn and share with each other, promoting their deep participation in agricultural product e-commerce.

4. The government can improve the support policies for agricultural product e-commerce, promote favorable policies, enhance farmers' confidence in agricultural product e-commerce, and reduce farmers' risk expectations.

Although many scholars have studied the adoption behavior of digital agricultural technology, there is a relative lack of research on the dynamics and complexity of the adoption behavior of agricultural e-commerce, especially in the qualitative analysis of the degree of adoption. This study provides new empirical evidence for the dynamic characteristics of the adoption process by discovering the differences in different influencing factors at different stages of adoption behavior. In addition, this study found that there are differences in the influencing factors of farmers' adoption behavior between Wuchang City and other regions, which proves that the performance of influencing factors has regional differences. This study can help international scholars identify key influencing factors in different regional contexts and provide more comprehensive empirical support for the development and policy-making of global agricultural e-commerce.

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