Research on the Use Behavior of Agricultural Big Data in the Era of Intelligent Agriculture Based on UTAUT Model

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Abstract: The "14th Five-Year Plan" for big data industry points out that the country attaches great importance to the development of big data industry, and creating new advantages for the development of digital economy in the new era has become a strong support for the construction of national basic strategic resources. Digital enables the development of smart agriculture, and agricultural big data has become an important engine to drive the development of smart agriculture. Firstly, from the perspective of farmers, with the help of "smart agriculture platform" as the representative of agricultural big data research, and on the theoretical basis of the technology acceptance model, an empirical study was carried out on the use behavior of agricultural big data. Next, PLS algorithm was used to explore the relationship between the potential variables. The results showed that performance expectation, social influence and data quality had significant positive effects on the willingness to adopt agricultural big data. Convenience and adoption intention have significant positive influence on the use behavior of agricultural big data.

Keywords: intelligent agriculture; UTAUT model; Agricultural big data; Behavior of use

1. Introduction

The combination of the new generation of information technology and agriculture, digital enabling agricultural production towards intelligent, intelligent. Intelligent agriculture takes agricultural biotechnology, information technology and intelligent equipment as the main means, integrates and penetrates with agricultural production factors, and becomes the "booster" of agricultural production. It is the commanding peak of agricultural development in today's countries [1]. Agricultural big data is the core to support the development of modern smart agriculture. With the construction of the agricultural intelligent platform, the depth and breadth of farmers' participation in the agricultural big data platform has been increased unprecedentically. The agricultural big data platform is not only a tool for farmers to exchange experience and share real-time management technology, but also a means of information release and precise regulation for the government and enterprises. It has become an important carrier for management technology exchange, information sharing and market observation, with features of originality, timeliness, fragmentation and efficiency. Many literatures at home and abroad focus on the qualitative analysis of the functions and technologies of agricultural big data, and the empirical analysis of the use of agricultural big data by farmers needs to be studied. This paper studies the influence factors of farmers' use behavior on agricultural big data, analyzes the relationship between potential variables of cognition level, adoption intention and use behavior, and focuses on the synergy between agricultural big data and agricultural production,

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which will promote the transformation and upgrading of agricultural digitization, informatization and brand, and provide enlightenment and reference for the development of smart agriculture.

2. Research model and research hypothesis

2.1 Research Model

This paper selects the UTAUT model of Venkatesh and Davis et al. (2003) as the basic model, and improves it to form the final model. According to the original model of the integrated technology acceptance model, Zheng Jixing et al. 's research on farmers' adoption of new technologies [2], this paper firstly selects four original external factors, namely, performance expectation, social impact, effort expectation and convenience. Considering the research object of this paper -- intelligent agriculture platform, according to the research of Chen Limei et al. [3], the paper proposes the influence of information quality on the adoption intention. Information quality is the subjective judgment of farmers on the merits of the information of the agricultural big data platform [4]. Farmers need to judge whether the platform information is useful to themselves and whether the information is scientific and timely. Farmers are very concerned about the quality of agricultural big data. Therefore, a new latent variable of "data quality" was added in this paper to make the structural model more perfect and more suitable for the research subject [5].

2.2 Research theory and hypothesis

PLS algorithm is mainly used for analysis in this study [6]. The main considerations for the selection of PLS algorithm are as follows: the first is suitable for small sample size, the second is suitable for non-normal distribution, the third pair of scale requirements are loose, and the fourth can deal with more complex structural equation model.

In this paper, performance expectation refers to the improvement of farmers' performance after using the smart agriculture platform [7]. Performance expectations can reflect farmers' cognitive evaluation of the smart agriculture platform. If farmers have a deep understanding and positive evaluation of the smart agriculture platform, they will have a greater chance to use the platform eventually. On the contrary, farmers have a negative evaluation of the platform, and their subjective behavior will reduce the probability of using the platform [8].

Research hypothesis 1: Performance expectation has a significant positive impact on the willingness to adopt agricultural big data

Effort expectation refers to how much effort farmers need to make in exchange for the services of new technologies [9]. Some farmers in this paper need to make efforts to learn and use the smart agriculture platform. In the special field of agriculture, farmers have certain limitations in the use of the agricultural big data platform. Will prevent farmers from using smart agriculture platforms.

Research hypothesis 2: Effort expectation has a significant negative effect on the willingness to adopt agricultural big data

Social influence refers to the fact that farmers are influenced by the groups around them when choosing the smart agriculture platform. For example, opinions from relatives, neighboring households, industry authorities, and large growers will affect farmers' willingness to adopt the smart agriculture platform [10].

Research hypothesis 3: Social influence has a significant positive impact on the willingness to adopt agricultural big data

The quality of agricultural big data is the basis of the agricultural big data platform. In this paper, data quality refers to whether the data provided by the intelligent agriculture platform is authentic and timely, and whether farmers have subjective evaluation on its merits and demerits. If the subjective evaluation result is good, the willingness to adopt will be stronger, and vice versa.

Research hypothesis 4: Data quality has a significant positive impact on the willingness to adopt agricultural big data

Convenience conditions refer to the conditions of the environment when the smart agriculture platform is used. Whether it can support the use of the smart agriculture platform is a kind of objective conditions, such as network, infrastructure, terminal and so on. These factors will affect farmers' behavior of using the smart agriculture platform.

Research hypothesis 5: Convenience has a significant positive impact on the use behavior of agricultural big data

Farmers' willingness to adopt the smart agriculture platform will affect their use behavior. As a key factor influencing whether farmers will use the smart agriculture platform, its significance is whether farmers actively adopt and pursue the use of the platform or resist it in a negative attitude. If they have a positive attitude towards their adoption intention, they are more likely to use agri-smart platform, and vice versa.

Research hypothesis 6: Adoption intention has a significant positive impact on agricultural big data usage behavior

3. Research design

3.1 Questionnaire Design

The design of this questionnaire is mainly compiled according to the latent variables in the model, and the internationally accepted Likert five-level scoring method is adopted. The six variables of performance expectation, effort expectation, social impact, data quality, convenience and willingness to adopt are assigned 2-3 questions respectively, as shown in Table 1. Each question is scored on a scale of 1-5, with 5 representing complete agreement and 1 representing complete disagreement. There are 15 questions in total.

Table 1 Model variables and indicators

Name of variable	Observable variable
Performance Expectations (AA)	Use smart farming to get more agricultural advice
	Use smart agriculture to improve the efficiency of resource uti-

	lization
Expectation of Effort (BB)	Proficient in using mobile phones to surf the Internet
	Easy to remember the operation steps of intelligent agriculture landing
	The interaction with the smart agriculture platform is clear
Social Impact (CC)	The neighbor recommended smart farming
	Farmers recommend smart farming
Data Quality (DD)	The smart agriculture push is in line with local conditions
	Smart agriculture push information has timeliness
Convenience (EE)	The regional network is fast
	The service quality of smart agriculture is stable
Willingness to Adopt (FF)	We plan to use smart agriculture in the future
	Smart farming will be recommended to relatives and friends
Use Behavior (GG)	Smart agriculture has been used for relevant production learning
	Has helped relatives and friends use the smart agriculture platform

3.2 Data Collection

This research takes the "smart agriculture" platform as the research object, which has special push schemes for each place and rich agricultural service content. As a combination platform of the Internet of Things and agricultural big data, it can accurately conduct data collection, data analysis, early warning and monitoring, and provide decision-making services, etc., with a large number of data sources. This paper collected data through the combination of Internet and offline distribution. The research mainly targeted the users of Dalian smart agriculture platform. The questionnaire survey started from June 2022 and ended in September 2022, and lasted for 2 months.

4. Data analysis and hypothesis testing

4.1 Reliability and validity test

Reliability analysis of the scale is the intrinsic quality of the measurement model. In order to ensure good reliability and validity of this study, the reliability analysis of 7 variables was carried out in this paper, and Cronbach's Alpha value was used for testing. Table 2 shows that the Cronbach's Alpha coefficients of social influence and convenience are 0.690 and 0.671, which meet the general reliability standard. The Cronbach's Alpha coefficients of other variables are above 0.7, meeting the requirements of statistical principles. Therefore, this scale can be considered to have good reliability.

Test of convergent validity: The test of convergent validity can be evaluated by factor loading, combination reliability and mean variance extraction value. In this paper, the minimum factor load of B3 is 0.789, and all factor loads meet the standards, so it can be considered that the factor load of the measurement model is ideal. Secondly, combination reliability refers to the internal consistency of the measured item, and the larger the value, the better. It is generally believed that the combination reliability value is greater than 0.7, and the measured item can be considered to have a good combination reliability. In this paper, the combined reliability is greater than 0.7, so it can be considered that the measurement model has good internal consistency. The mean variance extraction value refers to how much variation explained in the potential variable comes from the measured items. The larger the AVE value, the higher the degree to which the potential variable can be explained. It is generally believed that the model greater than 0.5 has good quality. In this study, AVE values are all greater than 0.5, so it is judged that the measurement model has ideal convergent validity.

Table 2 Convergence validity of the measurement model

Latent variable	multi-item	Load of factor	CR	AVE	Cronbach's Alpha
Expectations of performance	A1	0.868	0.876	0.779	0.718
	A2	0.897			
Strive to expect	B1	0.817	0.842	0.639	0.720
	B2	0.792			
	B3	0.789			
Social impact	C1	0.884	0.866	0.763	0.690
	C2	0.863			
Quality of data	D1	0.875	0.876	0.779	0.717
	D2	0.891			
Conditions of convenience	E1	0.872	0.859	0.752	0.671
	E2	0.863			
Willingness to adopt	F1	0.915	0.918	0.848	0.822
	F2	0.927			
Behavior of use	G1	0.915	0.908	0.831	0.796
	G2	0.908			

4.2 Overall goodness of fit test

First of all, the smaller the SRMR value of the absolute goodness of fit index is, the better the fit degree of the model will be. Generally, it is considered in statistical principles that the model fit degree is reasonable if it is less than 0.1, and the stricter requirement is less than 0.08. Secondly, the indexes d_ULS and d_G in the perfect adaptation index were proposed by Dijkstra and Henseler. If the adaptation standard of d_ULS and d_G is less than 0.95, it can be considered that the fit is good. According to Bentler and Bonett et al., the value of NFI ranges from 0 to 1, and the closer the value is to 1, the better the fitting degree is. If the value is greater than 0.7, it can be considered as having a good fitting degree. Table 3 has been observed through several corrections, among which, except for the canonical adaptation index NFI, which is close to the fitness, the other evaluation indexes meet all the standards, and the model's fitness is excellent, indicating that this model has a good fit with the survey data.

Table 3 Test table of overall fit degree

Category of Indicators	Index of evaluation	Standard of adaptation	Results of inspection	Fit of model
Absolute goodness of fit	SRMR	<0.08	0.075	good
Perfect fit index	d_ULS	<0.95	0.672	good
	d_G	<0.95	0.672	good
Specification adaptation index	NFI	>0.7	0.657	Close to the

4.3 Path Coefficient

By observing Table 4, we can know the path coefficient and significance of the research model in this survey, in which T value is used to evaluate whether the path coefficient is significant. The number of subsamples in this survey is 5000, which follows the normal distribution and conforms to the large sample in statistics. According to Gosset, an American statistician, and the principle of statistics, the following is proposed: 1.64 < = | t | < 1.96, mean significant at 0.10 significant level; 1.96 < = | t | < 2.58, mean significant at 0.05 significant level; | t | > = 2.58, indicated in the 0.01 significance level significantly. Therefore, the test results of this paper are as follows: the T-values of performance expectation -- adoption intention, social influence -- adoption intention, convenience -- use behavior, and adoption intention -- use behavior are 3.865, 5.883, 5.072, and 3.118, respectively, with P less than 0.01. Therefore, the results of hypothesis 1, hypothesis 3, hypothesis 5, and hypothesis 6 are supported. The path coefficient analysis of the variables showed that the path coefficient of performance expectation on the adoption intention was 0.273, and the path coefficient of social influence on the adoption intention was 0.616, which was significant at the level of 0.01. It was concluded that performance expectation had a positive correlation with the adoption intention of smart agriculture. The social influence has a positive correlation with the adoption intention of smart agriculture, and the social influence has a stronger impact on the adoption intention. Hypothesis 1 and hypothesis 3 are valid. At the same time, the path coefficient of convenience on use behavior is 0.552, and the path coefficient of adoption intention on use behavior is 0.356, which is significant at the level of 0.01. Therefore, both convenience condition and adoption intention are positively correlated with use behavior, and the influence of convenience condition on use behavior is stronger. Therefore, hypothesis 5 and hypothesis 6 are valid. By observing T and P values in Table 4.7, we can see that there is no significant correlation between latent variable effort expectation and adoption intention, so hypothesis 2 is not valid. The increased latent variable data quality has no significant relationship with the adoption intention, so hypothesis 4 is not valid.

Table 4 Path coefficients and research hypothesis testing results

hypothesis	Path coefficient	T	P	testing results
Hypothesis 1	0.273	3.865	0.000	support
Hypothesis 2	0.021	0.245	0.807	Not supported
Hypothesis 3	0.616	5.883	0.000	support
Hypothesis 4	0.063	0.793	0.428	Not supported
Hypothesis 5	0.552	5.072	0.000	support
Hypothesis 6	0.356	3.118	0.002	support

5. Conclusion and revelation

This paper takes the smart agriculture platform as the research object, based on the improved integrated technology acceptance model (UTAUT), and analyzes the behavioral characteristics of farmers from the perspective of their cognition of smart agriculture. The empirical results show that:

Performance expectation (AA) and social influence (CC) had a significant positive effect on adoption intention (FF), and performance expectation (AA) and social influence (CC) were the pre-influencing factors of behavioral attitude.

The willingness to adopt (FF) and convenience (EE) had a significant positive effect on the use behavior (GG), and the willingness to adopt (FF) and convenience (EE) were important factors affecting the use behavior (GG).

Based on the above research conclusions, the following suggestions are proposed:

First, improve the usefulness and applicability of agricultural big data. Through the above analysis, it can be seen that performance expectation (AA) has a significant positive correlation with adoption intention (FF). When developing agricultural big data related platforms, the government and relevant operating departments should most consider big data service projects that can bring practical and effective to farmers, so that farmers are willing to try agricultural big data service projects at first. In the later stage, word of mouth will be used to improve the application level of agricultural big data.

Second, increase the use of agricultural big data publicity efforts to popularize education. According to the research conclusion, social influence has a significant positive correlation with the adoption intention. Relevant government departments can take targeted publicity according to local areas and improve farmers' cognition and recognition of agricultural big data through multi-dimensional, multi-dimensional and high-frequency publicity actions.

Third, provide a convenient and efficient environment for the use of agricultural big data. Improve the network infrastructure in rural areas, reduce the difficulty coefficient required in the use of agricultural big data, and efficiently assist farmers in related production, operation and decision-making management.

Project

Project name: Study on the countermeasures of developing health Industry in Dalian

Unit: Dalian Polytechnic University

Author: Wu Xianyun

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