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Research on the farmers' agricultural digital service use behavior under the rural revitalization strategy—Based on the extended technology acceptance model

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The effective use of agricultural digital services can promote the transformation of agricultural production methods and actively promote the development of agricultural economy. However, in the process of agricultural production and operation, farmers are difficult to use agricultural digital services and are still at a disadvantage in the use of information. The rapid development and promotion of agricultural digital services provide opportunities for farmers to cross the "digital divide" and obtain "data dividend." Based on the extended technology acceptance model, this paper uses the partial least squares structural equation model to empirically analyze the key influencing factors of farmers' agricultural digital service use behavior. The research shows that farmers' agricultural digital use behavior is mainly affected by two key factors: adoption intention and facility conditions. Among them, adoption intention has a more significant impact on use behavior. At the same time, adoption intention is affected by performance expectation, social influence and data quality, which is an important pre-factor affecting behavior.

KEYWORDS

agricultural digital service, extended technology acceptance model, adoption intention, PLS-SEM, facility conditions

1 Introduction

The effective use of agricultural digital services can promote the transformation of agricultural production methods and actively promote the development of agricultural economy (Qin et al., 2022). However, in the process of agricultural production and operation, farmers are difficult to use agricultural digital services and are still at a disadvantage in the use of information (Dai et al., 2023). The rapid development and promotion of agricultural digital services provide opportunities for farmers to cross the 'digital divide' and obtain 'data dividend'.

Agricultural digitalization is the strategic direction and important content of agricultural and rural modernization in the new era (Jayne et al., 2019; Steinke et al., 2020). In January 2020, China's Ministry of Agriculture and Rural Affairs and the Central Network Information Office jointly issued the "Digital Agriculture and Rural Development Plan (2019–2025)" to fully deploy agricultural digitization. The outline of China's "14th Five-Year Plan" also clearly stated that it is necessary to accelerate the development of smart agriculture and promote the digital transformation of agricultural production, operation and management services. The Central Document No. 1 of 2022 further emphasized the development of smart agriculture and the integration of information technology and agricultural machinery and agronomy. At present, under the background of comprehensively promoting rural revitalization, following the law of modern agricultural development, China urgently needs to accelerate the development of agricultural digitalization driven by digital technology (Rotz et al., 2019; Liu et al., 2022b).

In recent years, academic research on industrial digitization has been increasing. In general, industrial digitization refers to the use of digital technology to upgrade business in traditional industries to improve production quantity and efficiency (Abbasi et al., 2022), including architecture guidance, data-driven, process integration, and ecological formation (Tseng et al., 2020). It is embodied in the form of factor digitization, process digitization and product digitization (Gao et al., 2022). Agricultural digitization refers to the digitization of agricultural elements and the management of agricultural elements by means of digitization (Remondino and Zanin, 2022). It mainly focuses on the following four aspects: First, the research perspective of agricultural digitization. Scholars have focused on the in-depth discussion of agricultural digitization from perspectives of technology the realization, technology empowerment, micro or macro economic management, and symbiotic theoretical analysis framework (Lioutas et al., 2021; Sukma and Leelasantitham, 2022b). The second is the influencing factors of agricultural digitization (Carmela Annosi et al., 2020). The imperfect agricultural digital infrastructure, the lack of agricultural digital talents, the insufficient application of supply chain digital technology, and the weak application ability of agricultural management entities have restricted the process of agricultural digitization (Liu et al., 2022a). Big data application, information infrastructure, institutional support, value-driven agricultural industry, promotion of new agricultural business entities and technology enterprises (Sukma and Leelasantitham, 2022c), and consumer demand are the key factors driving agricultural digitization (Fielke et al., 2020). The third is the promotion path of agricultural digitization. We should strengthen the basic construction of technology, organization and environmental conditions, drive agricultural modernization with precision agriculture, rely on ' block chain + Internet of Things' technology to break the drawbacks of the original agricultural industry (Sukma and Leelasantitham, 2022b), improve the application level of digital technology in the agricultural industry (Sukma and Leelasantitham, 2022a), empower the agricultural industry chain, integrate the role of resource elements in each link of the agricultural industry chain, so as to accelerate the promotion of agricultural digitization (Tang and Chen, 2022). Fourth, the practice mode of agricultural digitization. The developed country practice modes include precision agriculture mode, government-enterprise cooperation digital agriculture mode, order agriculture mode, etc (Zhang et al., 2016). The domestic practice modes are initially manifested as digital agriculture mode with unique technology and application logic, agricultural insurance decision-making mode, agricultural whole industry chain mode, intelligent agriculture mode, etc. (Balezentis et al., 2023).

The existing literature mostly conducts qualitative analysis from the importance and technical realization of agricultural digitization (Jiang et al., 2022), but there are few empirical analyses on whether farmers use agricultural digitization services. The effective use of agricultural digitization plays a positive role in realizing the strategy of rural revitalization. As the basic unit of agricultural production in China, farmers are the main body of agricultural production. In the production and operation activities of farmers, they can also embody the synergistic relationship between agricultural digitization and agricultural production decision-making. Therefore, based on the perspective of farmers, this paper reveals the important factors affecting the use behavior of agricultural digitalization. Using the classical extended technology acceptance model, based on the user's perspective, this paper explores how factors such as performance expectation, effort expectation, social impact, perceived cost, data quality and facility conditions affect the adoption intention and use behavior of agricultural digitalization services from the cognitive level of farmers. Reveal the inherent laws and basic characteristics of farmers' digital service use behavior, in order to provide targeted and operable reference for the construction of agricultural digital sharing system and the formulation of supporting policies. In short, this study aims to accomplish two main objectives.

- To explain the transmission mechanism through extended technology acceptance model influence farmers' technology adoption behavior through intrinsic perceptions.
- To test whether there is a direct effect of facility conditions on technology adoption behavior.

The structure of the article is as follows: Section 2 summarizes the theory and hypotheses; Section 3 introduces the questionnaire and data source; Section 4 presents the results of the study. Section 5 summarises the conclusions, contributions, and provides some practical implications due to empirical findings.

2 Theory and hypotheses

2.1 Extended technology acceptance model

The extended technology acceptance model (E-TAM) is a classical theoretical paradigm for explaining and predicting human behavior in the fields of economic management and social psychology (Kamal et al., 2020). The theory is developed on the basis of seven theoretical paradigms (Abdullah and Ward, 2016), including social cognitive theory (SCT), rational behavior theory (TRA), planned behavior theory (TPB), technology fit theory (TTF), innovation diffusion theory (IDT), motivation theory (MT), compound TAM and TPB model (C-TAM-TPB). Through the description of the system, Venkatesh et al. (2003) puts forward the extended technology acceptance theory (Venkatesh et al., 2003), including four core constructs: performance expectations, individual expectations of information systems to help improve their job performance (Silva et al., 2019); effort expectancy, the individual's expectation of the degree of effort to master and use information systems (Rahi et al., 2019); social influence, the

recognition of this information system by people who feel important to them (Halevy et al., 2019); facility conditions, individuals believe that the existing organizations and technical facilities to support their use of this information system (Venkatesh et al., 2003).

According to the extended technology acceptance model, there is a high positive correlation between individual adoption intention and use behavior (Bock et al., 2005; Anderson and Agarwal, 2010). The stronger the individual's adoption intention, the higher the possibility of actual action (Angst and Agarwal, 2009). The three main variables of individual performance expectation, effort expectation and social impact work together on the adoption intention, and the facility conditions directly lead to the use behavior (Oliveira et al., 2016). In addition, many scholars' empirical studies have shown that data quality and perceived cost have a significant impact on the intention to use new information technology (Lai, 2004). Therefore, in this study, two variables of data quality and perceived cost are introduced in order to test the key influencing factors of agricultural digital use intention and behavior more comprehensively and reliably.

2.2 Research hypothesis

Based on the framework of Venkatesh et al., this study intends to empirically analyze the pre-influencing factors of farmers' adoption intention and use agricultural digital services (Venkatesh et al., 2003). Based on the extended technology acceptance model, farmers' adoption intention agricultural digital services will have an important impact on their use behavior. As a key influencing factor, adoption intention refers to the positive or negative behavior of farmers in the process of using agricultural digital services. Driven by positive adoption intention, farmers' agricultural digital use behavior will be more proactive (Verma and Sinha, 2018). At the same time, performance expectancy (PE) is an individual's belief that the use of new technologies will improve job performance and is regarded as the most powerful predictive tool (Brown et al., 2014). The performance expectation of farmers' digital use reflects their cognition and behavior towards agricultural digitization (Venkatesh et al., 2012). The deeper the farmers' cognition of digital performance expectations and the more positive the evaluation, the greater the possibility of using agricultural digitization (Faid et al., 2022). On the contrary, if farmers do not agree with the performance of agricultural digitization and evaluate it negatively, they are subjectively unwilling to use agricultural digitization services. Effort Expectancy refers to the time and energy that users need to pay when learning to use a new information technology system (Lutfi et al., 2022), that is, the degree of effort required to use an information system. In E-TAM, effort expectancy has a direct impact on farmers' adoption intention (Deng et al., 2010). Although the use of some rural agricultural digitization can bring changes in production and life to farmers, if there are too many and too high technical requirements for the use and acceptance of agricultural digitization platform systems and terminals, it will hinder the use of agricultural digitization for farmers with limited technical learning and use ability.

Therefore, whether the operation is simple or not is directly related to the adoption intention agricultural digitization. Social influence is the influence of groups who have used agricultural digitization on other farmers in the process of selecting and using agricultural digitization. In the process of agricultural production and management, many decisions of farmers will be influenced by the opinion leaders or authoritative people around them, such as local technical talents, large planting and breeding households, agricultural technical service personnel and their relatives and friends, etc. The adoption intention of farmers will be affected by the recommended behavior of the above people. Facility condition refers to the degree of support that the user's environment, organization and technical equipment perceived during the use of technology or services support their use of this information technology system. Venkatesh et al. (2012) have shown that users with the best Facility conditions will have a higher adoption intention and accept new technologies (Venkatesh et al., 2012). Facility condition in this study refers to farmers' perception of the facility condition required for the use of agricultural digitization and the completeness of various supporting technologies. At the same time, facility conditions provide objective conditions for the use of agricultural digitalization by farmers. Therefore, the use of agricultural digital services by farmers will also be affected by facility conditions. Based on the above analysis, this study proposes the following five hypotheses.

Hypothesis 1. (H1): Performance expectation has a significant positive impact on farmers' adoption intention agricultural digital services;

Hypothesis 2. (H2): Effort expectation has a significant negative impact on farmers' adoption intention agricultural digital services;

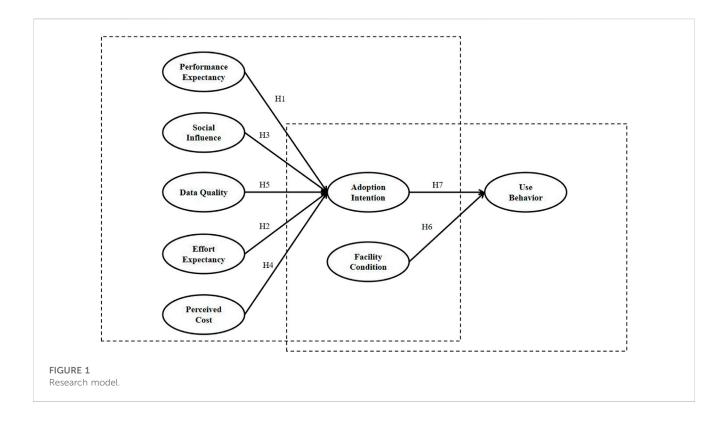
Hypothesis 3. (H3): Social impact has a significant positive impact on farmers' adoption intention agricultural digital services;

Hypothesis 4. (H4): Facility condition has a significant positive impact on farmers' use of agricultural digital services;

Hypothesis 5. (H5): Adoption intention has a significant positive impact on agricultural digital use behavior.

Data quality is the subjective judgment of users on the excellence or superiority of agricultural digitization, including the authenticity, scientificity, timeliness and comprehensiveness of agricultural digitization services (Zscheischler et al., 2022). Agricultural digitization is the basis of farmers' production and management. Therefore, the quality of agricultural digitization used by farmers, including weather, soil moisture, seedling condition, disaster and other data quality, is very important, which can help farmers improve the scientific nature of production decision-making and the fineness of management. Farmers' perception of the quality of agricultural digitization will affect their adoption intention, and unreliable digital services will have a negative impact on farmers and bring greater uncertainty. During the investigation, it was found that farmers were very concerned about the quality of agricultural digitization. Therefore, this study introduces data quality into the model as a key factor affecting farmers' intention to use agricultural digitization.

Perceived cost refers to all the costs perceived by individuals when purchasing products or services, including the cost of purchasing terminals and the cost of using agricultural



digitization. Research shows that cost factors have a significant impact on the adoption of new technologies. Under the longterm urban-rural dual system, farmers' income is relatively low, and they are more sensitive to perceived costs when using agricultural digitization. Therefore, the cost and price structure in the use of agricultural digitization will have an impact on farmers' intention to use. As mentioned above, the perceived cost is also an important factor in the extended E-TAM. Therefore, according to the nature of agricultural digitization, from the perspective of system quality and economic characteristics, data quality and perceived cost are taken as two variables that affect the adoption intention, and the technology acceptance model is further expanded, and the analysis framework and hypothesis to be tested are proposed. See Figure 1.

Hypothesis 6. (H6): Data quality has a significant positive impact on farmers' intention to use agricultural digitization;

Hypothesis 7. (H7): Perceived cost has a significant negative impact on farmers' intention to use agricultural digitization.

3 Methodology

3.1 Data collection

As an important agricultural province in China, Shaanxi has built a "Shaanxi Agricultural Digital Platform" in recent years. The platform aims at the characteristics of large spatial and temporal variation of key factors affecting crop growth such as soil fertility, salt content, pH, groundwater and salinity in Guanzhong Plain. The Internet of Things and digital technology collaboration system TABLE 1 Sample characteristics.

City	County	Frequency	Proportion (%)			
Weinan	Dali	112	24.1			
	Fuping	121	26.0			
Baoji	Qishan	115	24.7			
	Fengxiang	117	25.2			
Total		465	100			

can accurately collect and store data in real time, and provide solutions through data mining analysis. Therefore, this paper selects "Shaanxi Agricultural Digital Platform" as the research object and conducts field research in Shaanxi Province. The research group visited Weinan City and Baoji City in Shaanxi Province from September to October 2022. Two counties were selected from the two cities, and two villages were randomly selected from the two counties for investigation. The specific survey sample points are distributed as shown in Table 1. A total of 500 questionnaires were distributed, 482 questionnaires were collected, and 465 valid questionnaires were collected. The effective rate of the questionnaire was 93%.

3.2 Questionnaire design

To ensure the reliability and validity of the questionnaire, Questionnaire items should be developed in accordance with the following scientific processes, according to the research

TABLE 2 Measurement questionnaire.

Variable	ltem	Observable item			
Performance Expectancy	PE1	Using agricultural digital services saves agricultural production time			
	PE2	Using agricultural digital services saves agricultural production time			
	PE3	Can improve the family income			
Effort Expectancy	EE1	Agricultural digital platform is simple and convenient to operate			
	EE2	The interaction with the platform is clear			
Social Influence	SI1	Agricultural technology extension practitioners recommend the use of agricultural digitization services			
	SI2	Friends and family recommend digital agriculture services			
	SI3	Large farmers recommend the use of agricultural digital services			
Facility Condition	FC1	The service quality of agricultural digital platform is stable			
	FC2	It is fast to use agricultural digital platform			
	FC3	Internet coverage is excellent in my area			
Perceived Cost	PC1	I feel the terminal price is high			
	PC2	I feel the monthly fee is high			
	PC3	I feel the price of communication traffic is high			
	PC4	I feel the price of subscription information service is too high			
Data Quality	DQ1	Agricultural digital platform service has authenticity			
	DQ2	Agricultural digital platform service has accuracy			
	DQ3	Agricultural digital platform service has timeliness			
	DQ4	Agricultural digital platform service is easy to understand			
Adoption Intention	AI1	I plan to use agricultural digital services in the future			
	AI2	I intend to recommend relatives and friends to use agricultural digital services			
	AI3	I am willing to use agricultural digital services frequently			
Use Behhavioral	UB1	I have used agricultural digital services to start my business			
	UB2	I help family and friends use agricultural digitization services			

recommendations of Churchill (1979): (a) Variable items should be organized according to the relevant literature. (b) Measurement items should be back-translated. In this paper, the internationally accepted Likert 7-level scoring method is used to measure the latent variables such as performance expectation, effort expectation, social influence, facility condition, perceived cost, data quality, and adoption intention. The variable assignments are increasing in turn. Among them, completely disagree with "1", neither agree nor disagree with "4," and completely agree with "7." Based on the classic scale, the questionnaire items of this survey are further revised according to the characteristics of farmers and the "Shaanxi Agricultural Digital Platform." The measurement of performance expectation, effort expectation, social impact and facility conditions comes from the scale of Venkatesh et al. (2012), the measurement of perceived cost comes from the scale of Liu et al. (2001), the measurement of data quality comes from the scale of Wang and Strong (1996), and the

measurement of adoption intention and use behavior comes from the scale of Venkatesh et al. (2003). The questionnaire covers all the contents required by this study. The questions involve eight latent variables (performance expectation, effort expectation, social influence, facility condition, perceived cost, data quality, adoption intention and use behavior). The latent variables and the observable variables included and their sources are shown in Table 2.

3.3 Technical analysis

The variables studied in this paper are many latent variables that are difficult to measure directly, such as performance expectation, effort expectation, social influence, facility condition and so on. Therefore, structural equation model is used to carry out empirical analysis. In this paper, SmartPLS is used to analyze the data (Joo and Sang, 2013). Compared with

TABLE 3 Reliability and validity.

Variables	ltems	Loadings	Cronbach's α	CR	AVE
Adoption Intention	AI1	0.817	0.763	0.863	0.678
	AI2	0.821	-		
	AI3	0.833			
Data Quality	DQ1	0.882	0.905	0.934	0.779
	DQ2	0.916			
	DQ3	0.886			
	DQ4	0.845			
Effort Expectancy	EE1	0.956	0.9	0.952	0.909
	EE2	0.95			
Facility Condition	FC1	0.838	0.812	0.888	0.725
	FC2	0.858			
	FC3	0.858			
Perceived Cost	PC1	0.897	0.883	0.919	0.739
	PC2	0.891			
	PC3	0.81			
	PC4	0.838	-		
Performance Expectancy	PE1	0.888	0.819	0.893	0.737
	PE2	0.903			
	PE3	0.779	-		
Social Influence	SI1	0.842	0.842	0.893	0.677
	SI2	0.849			
	SI3	0.775			
	SI4	0.823	-		
Use Behhavioral	UB1	0.949	0.895	0.95	0.905
	UB2	0.954			

Note: CR, composite reliability; AVE, average variance extracted; VIF, variance inflation factors.

AMOS, the software has the following advantages: it can solve the problem of difficult or unrecognized model identification caused by too many measurement indicators, non-positive definite matrices, and coefficients greater than 1; in terms of fitting, it can solve the problem of insufficient model goodness of fit caused by too complex model. In addition, the software can solve the problem of parameter estimation bias caused by serious nonnormal distribution of data.

3.4 Common method bias

The Haman single factor test method was used to detect the common method bias of the survey data, and all the measurement items of the questionnaire were analyzed by principal component analysis. The maximum variance interpretation rate of the first principal component without rotation was 32.433%, which was lower than 50%, indicating that the common method bias had no serious impact on this study.

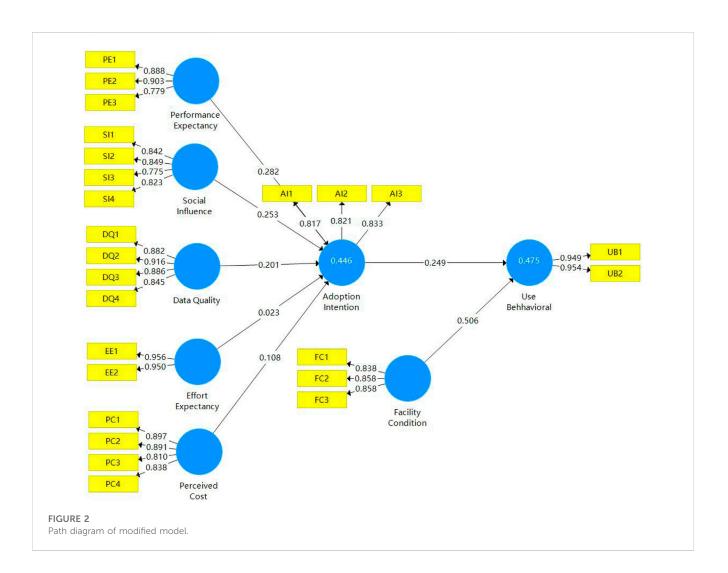
3.5 Reliability and validity

Reliability analysis mainly refers to the internal quality of the measurement model. This paper first analyzes the reliability of the eight main variables, and uses the combined reliability (CR), the average variance extraction value (AVE) and the Cronbach α coefficient as the reliability and validity test indicators. Table 3 shows that the combined reliability (CR) of the eight main variables is above 0.8, and the Cronbac' α coefficient is greater than 0.7, so the survey data has good reliability. It is generally believed that the scale has good structural validity when the combined reliability (CR) is greater than 0.7 and the average

Variables	1	2	3	4	5	6	7	8
1. Adoption Intention	0.824	0.540	0.321	0.794	0.429	0.730	0.720	0.680
2. Data Quality	0.451**	0.883	0.352	0.574	0.275	0.430	0.502	0.586
3. Effort Expectancy	0.268**	0.313**	0.953	0.455	0.424	0.293	0.318	0.514
4. Facility Condition	0.623**	0.499**	0.387**	0.851	0.526	0.611	0.645	0.765
5. Perceived Cost	0.365**	0.246**	0.373**	0.453**	0.86	0.437	0.404	0.434
6. Performance Expectancy	0.578**	0.370**	0.251**	0.500**	0.379**	0.859	0.830	0.437
7. Social Influence	0.583**	0.442**	0.281**	0.540**	0.362**	0.693**	0.823	0.452
8. Use Behhavioral	0.564**	0.524**	0.462**	0.661**	0.388**	0.375**	0.398**	0.951

TABLE 4 Discriminant validity—Fornell-Larcker Criterion and Heterotrait-Monotrait Ratio.

Note: **Correlation is significant at the 0.01 level (2-tailed), Bold diagonal entries are square root of AVEs, Heterotrait-Montrait ratios (HTMT) (Underlined) are below 0.85.



variance extraction (AVE) is greater than 0.5. This scale is designed on the basis of previous scales and research results. In the process of design, it is revised by combining the opinions of experts and farmers, so it can be concluded that the content validity of this scale is good. The results of the Fornell-Larcker Criterion (Table 4) show that the AVE square roots of the eight latent variables in this study are greater than the correlation coefficients between the variable and other variables, indicating that the measurement model has good discriminant validity. Heterotrait-Montrait ratios (HTMT) (Underlined) are below 0.85.

Hypothesis	Effect	Path	Path coefficient	Lower (2.5%)	Upper (97.5%)	t-statistics	<i>p</i> -value	Decision
Direct relationships								
H1	Direct	PE -> AI	0.28	0.136	0.417	3.944	0.000***	Accept
H2	Direct	SI -> AI	0.251	0.104	0.402	3.375	0.001***	Accept
Н3	Direct	EE -> AI	0.023	-0.083	0.131	0.408	0.683	Refuse
H4	Direct	FC -> UB	0.507	0.401	0.607	9.696	0.000***	Accept
Н5	Direct	AI -> UB	0.249	0.086	0.383	3.249	0.001***	Accept
H6	Direct	DQ -> AI	0.203	0.064	0.351	2.721	0.007**	Accept
H7	Direct	PC -> AI	0.113	0.006	0.221	1.954	0.051	Refuse
SRMR composite model = 0.047		1	I		1	1		
$R^{2}_{AI} = 0.437; Q^{2}_{AI} = 0.285$								
$R^{2}_{UB} = 0.471; Q^{2}_{UB} = 0.424$								

TABLE 5 Results of hypothesis testing.

Note: Significant level: p < 0.10; *p < 0.05; **p < 0.01; ***p < 0.001.

4 Results

Figure 2 and Table 5 show the standardized path coefficient and significance of the farmers' agricultural digitization services use model. The results show that the standardized path coefficients of performance expectation and social influence on adoption intention are 0.28 and 0.251, respectively, and are significant at the confidence levels of 1%. Therefore, performance expectation and social influence have a positive correlation with farmers' adoption intention agricultural digitalization, so Hypothesis 1 and Hypothesis 3 are established. The influence of effort expectation on adoption intention is not significant, so Hypothesis 2 is not true. Among the increased latent variables, there is no correlation between perceived cost and adoption intention, so Hypothesis 4 is not established; Data quality has a positive correlation with farmers' adoption intention agricultural digitization, and is significant at the 1% confidence level, so Hypothesis 5 is established.

Through the use of agricultural digital platform, it can help farmers to obtain more accurate and timely information, help farmers to carry out planting management, improve planting quality, and then improve income level. Due to the social characteristics of rural areas, farmers are vulnerable to the influence of surrounding farmers in the use of agricultural digitization; the higher the quality of agricultural digitization, the less time and energy farmers spend on data screening. The authenticity, effectiveness, accuracy and timeliness of digitization will help farmers' agricultural production. Therefore, the higher the quality of data, the more willing farmers are to use agricultural digitization. The current Shaanxi agricultural digital platform is easy to use by farmers and easy to apply to agricultural production practice due to its friendly and simple operation interface. Empirical research shows that perceived cost has no effect on farmers' adoption intention, and there is no correlation between them. This conclusion is puzzling. One possible explanation is that agricultural digitization is still in the trial stage of promotion, and most of them are free for farmers to use, so this variable has no effect on adoption intention. Secondly, there is a positive correlation between adoption intention and facility conditions on agricultural digital use behavior at the 1% confidence level. Hypothesis 6 and Hypothesis 7 are supported, and the original hypothesis is established. Among them, the adoption intention agricultural digitization has the most significant impact on farmers' digital use behavior, and positive adoption intention has a strong positive effect on the use behavior. The service quality, network coverage and speed of agricultural digitization have a positive impact on the use behavior of farmers' agricultural digitization. This result is consistent with most empirical research results. Farmers feel that the facility condition of use conditions will encourage them to use agricultural digitization.

The above research shows that the three variables of farmers' performance expectation, social impact and data quality of agricultural digitization are the pre-factors that affect the adoption intention. Further, these three variables will affect the use behavior through the adoption intention. In addition, the key variable facility conditions in the extended technology acceptance model have a direct positive impact on farmers' use behavior.

5 Discussion

5.1 Theoretical implications

First, further enhance the usefulness of agricultural digitization in rural areas. The research shows that performance expectation has a positive correlation with adoption intention, and the effect is the most significant. Therefore, in the process of developing and optimizing agricultural digital platforms, governments, mobile operators and relevant agricultural departments should consider digital service projects that can bring tangible benefits to farmers (Dong et al., 2022b).

Second, further improve the quality of agricultural digitization, ensure that the digitization is objective, accurate, timely, easy to

understand and comprehensive, improve the supply capacity and analysis and utilization capacity of agricultural digitization such as climate, fertility and epidemic situation, and more effectively assist decision-making and production management (Dong et al., 2022a).

Third, further improve the use environment of agricultural digitization, focus on improving the operability and effectiveness of agricultural digitization solutions, and efficiently improve the efficiency of assisting farmers in solving wheat production and operation. Fourth, increase publicity and focus on word-of-mouth publicity. It can carry out publicity for small and medium-sized farmers, increase publicity frequency, delay publicity time, expand publicity channels, enrich delivery forms and other methods to carry out multi-directional and three-dimensional publicity, and improve farmers' awareness of agricultural digitization.

5.2 Managerial implications

Information gap is a key factor hindering the implementation of rural revitalization strategy and digital China strategy, so it is necessary to promote the transformation of information industry to traditional agriculture (Sukma and Leelasantitham, 2022c). Make information technology become an important driving force to improve the modernization of rural governance system and governance capacity, and exert the diffusion effect of information technology innovation, the spillover effect of information and knowledge, and the universal benefit effect released by digital technology, so as to promote the transformation of agricultural digitalization, the implementation of rural service digitalization and the play of farmers' digital power. However, on the one hand, modern information technology has promoted the rapid development of digital economy and information society (Sukma and Leelasantitham, 2022b), on the other hand, it has intensified the gap between urban and rural areas to a certain extent. Moreover, the low level of input in information resources, the fragmentation of rural information infrastructure, the fragility of villagers' information consumption ability, and the weak state of villagers' ability to obtain information have further widened the information gap in digital rural construction (Sukma and Leelasantitham, 2022a). The expansion of the information gap has compressed the opportunity of rural access to information resources, aggravated the crisis of "digital survival" of villagers, and then led to many practical symptoms of digital rural construction such as the project lag of digital agricultural production, regional differences in the development of rural e-commerce, the solidification of digital service application, and the gap between generations of digital culture consumption. There is no doubt that the situation of rural information infrastructure and farmers' information ability determine the horizontal expansion and vertical deepening of rural digitalization. The existence and expansion of information gap will accelerate the further expansion of the gap between tiers, regions and urban and rural areas, and further develop into information differentiation, which in turn accelerates the polarization of the rich and the poor and the social differentiation.

6 Conclusion

This paper takes Shaanxi agricultural digitization platform as the research object, based on the mature classical extended technology

acceptance model in the field of information technology, starting from the cognitive psychological level of farmers, taking into account the characteristics of agricultural digitization, including two variables of perceived cost and data quality, and expanding the external variables of the extended technology acceptance model, in order to reveal the key influencing factors of the adoption intention and use behavior of agricultural digitization, and the transmission path of these key factors. Taking the exemplary Shaanxi agricultural digital platform as the research object, a field survey was conducted in Weinan City and Baoji City of Shaanxi Province. The situation of wheat growers in the two cities was obtained through household survey, and SmartPLS was used for analysis. The empirical results show that farmers ' agricultural digital use behavior is mainly affected by two key factors: adoption intention and facility conditions, among which adoption intention has a more significant impact on use behavior. Performance expectancy, social influence and data quality are important antecedents of behavioral behaviors.

7 Limitations and future research directions

There is still room for further discussion in this study, which is mainly reflected in the following aspects: first, the use of crosssectional data in this study cannot reflect the dynamic role of agricultural digitization and farmers' agricultural digital service use behavior; second, there may be differences in resource endowment characteristics and technology use behavior in different regions. Due to the limitation of sample size, this study failed to distinguish and further explore.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent from the participants was not required to participate in this study in accordance with the national legislation and the institutional requirements.

Author contributions

Conceptualization, HD and BW; methodology, HD; software, BW; validation, BW; formal analysis, BW; investigation, HD; resources, HD; data curation, HD; writing—original draft preparation, HD; writing—review and editing, HD; visualization, HD; supervision, BW; project administration, BW; funding acquisition, BW. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

Author BW and HD were employed by Shaanxi Provincial Land Engineering Construction Group Co.

References

Abbasi, R., Martinez, P., and Ahmad, R. (2022). The digitization of agricultural industry – A systematic literature review on agriculture 4.0. *Smart Agric. Technol.* 2, 100042. doi:10.1016/j.atech.2022.100042

Abdullah, F., and Ward, R. (2016). Developing a general extended technology acceptance model for E-learning (GETAMEL) by analysing commonly used external factors. *Comput. Hum. Behav.* 56, 238–256. doi:10.1016/j.chb.2015.11.036

Anderson, C. L., and Agarwal, R. (2010). Practicing safe computing: A multimethod empirical examination of home computer user security behavioral intentions. *MIS Q.* 34, 613–643. doi:10.2307/25750694

Angst, C. M., and Agarwal, R. (2009). Adoption of electronic health records in the presence of privacy concerns: The elaboration likelihood model and individual persuasion. *MIS Q.* 33, 339. doi:10.2307/20650295

Balezentis, T., Zickiene, A., Volkov, A., Streimikiene, D., Morkunas, M., Dabkiene, V., et al. (2023). Measures for the viable agri-food supply chains: A multi-criteria approach. *J. Bus. Res.* 155, 113417. doi:10.1016/j.jbusres.2022.113417

Bock, G.-W., Zmud, R. W., Kim, Y.-G., and Lee, J.-N. (2005). Behavioral intention formation in knowledge sharing: Examining the roles of extrinsic motivators, social-psychological forces, and organizational climate. *MIS Q.* 29, 87–111. doi:10.2307/25148669

Brown, S. A., Dennis, A. R., and Venkatesh, V. (2014). Predicting collaboration technology use: Integrating technology adoption and collaboration research. J. Manag. Inf. Syst. 27, 9–54. doi:10.2753/MIS0742-1222270201

Carmela Annosi, M., Brunetta, F., Capo, F., and Heideveld, L. (2020). Digitalization in the agri-food industry: The relationship between technology and sustainable development. *Manag. Decis.* 58, 1737–1757. doi:10.1108/MD-09-2019-1328

Dai, X., Chen, Y., Zhang, C., He, Y., and Li, J. (2023). Technological revolution in the field: Green development of Chinese agriculture driven by digital information technology (DIT). *Agriculture* 13, 199. doi:10.3390/agriculture13010199

Deng, L., Turner, D. E., Gehling, R., and Prince, B. (2010). User experience, satisfaction, and continual usage intention of IT. *Eur. J. Inf. Syst.* 19, 60–75. doi:10. 1057/ejis.2009.50

Dong, H., Wang, B., Han, J., Luo, L., Wang, H., Sun, Z., et al. (2022a). Understanding farmers' eco-friendly fertilization technology adoption behavior using an integrated S-O-R model: The case of soil testing and formulated fertilization technology in shaanxi, China. . Frontiers in Environmental Science 10. Available at: https://www.frontiersin.org/articles/10.3389/fenvs.2022.991255 (Accessed November 5, 2022).

Dong, H., Wang, H., and Han, J. (2022b). Understanding ecological agricultural technology adoption in China using an integrated technology acceptance model—theory of planned behavior model. *Front. Environ. Sci.* 10, 927668. doi:10. 3389/fenvs.2022.927668

Faid, A., Sadik, M., and Sabir, E. (2022). An agile ai and IoT-augmented smart farming: A cost-effective cognitive weather station. *Agriculture* 12, 35. doi:10.3390/agriculture12010035

Fielke, S., Taylor, B., and Jakku, E. (2020). Digitalisation of agricultural knowledge and advice networks: A state-of-the-art review. *Agric. Syst.* 180, 102763. doi:10.1016/j.agsy. 2019.102763

Gao, D., Li, G., and Yu, J. (2022). Does digitization improve green total factor energy efficiency? Evidence from Chinese 213 cities. *Energy* 247, 123395. doi:10.1016/j.energy. 2022.123395

Halevy, N., Kreps, T. A., and De Dreu, C. K. W. (2019). Psychological situations illuminate the meaning of human behavior: Recent advances and application to social

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influence processes. Soc. Personality Psychol. Compass 13, e12437. doi:10.1111/spc3. 12437

Jayne, T. S., Snapp, S., Place, F., and Sitko, N. (2019). Sustainable agricultural intensification in an era of rural transformation in Africa. *Glob. Food Secur.* 20, 105–113. doi:10.1016/j.gfs.2019.01.008

Jiang, Q., Li, J., Si, H., and Su, Y. (2022). The impact of the digital economy on agricultural green development: Evidence from China. *Agriculture* 12, 1107. doi:10. 3390/agriculture12081107

Joo, J., and Sang, Y. (2013). Exploring Koreans' smartphone usage: An integrated model of the technology acceptance model and uses and gratifications theory. *Comput. Hum. Behav.* 29, 2512–2518. doi:10.1016/j.chb.2013.06.002

Kamal, S. A., Shafiq, M., and Kakria, P. (2020). Investigating acceptance of telemedicine services through an extended technology acceptance model (TAM). *Technol. Soc.* 60, 101212. doi:10.1016/j.techsoc.2019.101212

Lai, T. L. (2004). Service quality and perceived value's impact on satisfaction, intention and usage of short message service (SMS). *Inf. Syst. Front.* 6, 353–368. doi:10.1023/B:ISFI.0000046377.32617.3d

Lioutas, E. D., Charatsari, C., and De Rosa, M. (2021). Digitalization of agriculture: A way to solve the food problem or a trolley dilemma? *Technol. Soc.* 67, 101744. doi:10. 1016/j.techsoc.2021.101744

Liu, C., Arnett, K. P., Capella, L. M., and Taylor, R. D. (2001). Key dimensions of web design quality as related to consumer response. *J. Comput. Inf. Syst.* 42, 70–82. doi:10. 1080/08874417.2001.11647041

Liu, W., Wei, S., Wang, S., Lim, M. K., and Wang, Y. (2022a). Problem identification model of agricultural precision management based on smart supply chains: An exploratory study from China. *J. Clean. Prod.* 352, 131622. doi:10.1016/j.jclepro. 2022.131622

Liu, W., Zhou, W., and Lu, L. (2022b). An innovative digitization evaluation scheme for spatio-temporal coordination relationship between multiple knowledge driven rural economic development and agricultural ecological environment—coupling coordination model analysis based on guangxi. *J. Innovation Knowl.* 7, 100208. doi:10.1016/j.jik.2022.100208

Lutfi, A., Saad, M., Almaiah, M. A., Alsaad, A., Al-Khasawneh, A., Alrawad, M., et al. (2022). Actual use of mobile learning technologies during social distancing circumstances: Case study of king faisal university students. *Sustainability* 14, 7323. doi:10.3390/su14127323

Oliveira, T., Thomas, M., Baptista, G., and Campos, F. (2016). Mobile payment: Understanding the determinants of customer adoption and intention to recommend the technology. *Comput. Hum. Behav.* 61, 404–414. doi:10.1016/j.chb.2016.03.030

Qin, T., Wang, L., Zhou, Y., Guo, L., Jiang, G., and Zhang, L. (2022). Digital technology-and-services-driven sustainable transformation of agriculture: Cases of China and the EU. *Agriculture* 12, 297. doi:10.3390/agriculture12020297

Rahi, S., Othman Mansour, M. M., Alghizzawi, M., and Alnaser, F. M. (2019). Integration of UTAUT model in internet banking adoption context: The mediating role of performance expectancy and effort expectancy. *J. Res. Interact. Mark.* 13, 411–435. doi:10.1108/JRIM-02-2018-0032

Remondino, M., and Zanin, A. (2022). Logistics and agri-food: Digitization to increase competitive advantage and sustainability. Literature review and the case of Italy. *Sustainability* 14, 787. doi:10.3390/su14020787

Rotz, S., Gravely, E., Mosby, I., Duncan, E., Finnis, E., Horgan, M., et al. (2019). Automated pastures and the digital divide: How agricultural technologies are shaping labour and rural communities. *J. Rural Stud.* 68, 112–122. doi:10.1016/j.jrurstud.2019. 01.023 Silva, S., Nuzum, A.-K., and Schaltegger, S. (2019). Stakeholder expectations on sustainability performance measurement and assessment. A systematic literature review. *J. Clean. Prod.* 217, 204–215. doi:10.1016/j.jclepro.2019.01.203

Steinke, J., Etten, J., Müller, A., Ortiz-Crespo, B., Gevel, J., Silvestri, S., et al. (2020). Tapping the full potential of the digital revolution for agricultural extension: An emerging innovation agenda. International Journal of Agricultural Sustainability. Available at: https://www.tandfonline.com/doi/abs/10.1080/14735903.2020.1738754 (Accessed March 2, 2023).

Sukma, N., and Leelasantitham, A. (2022a). A community sustainability ecosystem modeling for water supply business in Thailand. *Front. Environ. Sci.* 10. doi:10.3389/ fenvs.2022.940955

Sukma, N., and Leelasantitham, A. (2022b). From conceptual model to conceptual framework: A sustainable business framework for community water supply businesses. *Front. Environ. Sci.* 10. doi:10.3389/fenvs.2022.1013153

Sukma, N., and Leelasantitham, A. (2022c). The influence and continuance intention of the E-government system: A case study of community water supply business. *Front. Environ. Sci.* 10. doi:10.3389/fenvs.2022.918981

Tang, Y., and Chen, M. (2022). The impact of agricultural digitization on the highquality development of agriculture: An empirical test based on provincial panel data. *Land* 11, 2152. doi:10.3390/land11122152 Tseng, M.-L., Chang, C.-H., Lin, C.-W. R., Wu, K.-J., Chen, Q., Xia, L., et al. (2020). Future trends and guidance for the triple bottom line and sustainability: A data driven bibliometric analysis. *Environ. Sci. Pollut. Res.* 27, 33543–33567. doi:10.1007/s11356-020-09284-0

Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Q.* 27, 425. doi:10.2307/30036540

Venkatesh, V., Thong, J. Y. L., and Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Q.* 36, 157. doi:10.2307/41410412

Verma, P., and Sinha, N. (2018). Integrating perceived economic wellbeing to technology acceptance model: The case of mobile based agricultural extension service. *Technol. Forecast. Soc. Change* 126, 207–216. doi:10.1016/j.techfore.2017.08.013

Wang, R. Y., and Strong, D. M. (1996). Beyond accuracy: What data quality means to data consumers. J. Manag. Inf. Syst. 12, 5–33. doi:10.1080/07421222.1996.11518099

Zhang, Y., Wang, L., and Duan, Y. (2016). Agricultural information dissemination using ICTs: A review and analysis of information dissemination models in China. *Inf. Process. Agric.* 3, 17–29. doi:10.1016/j.inpa.2015.11.002

Zscheischler, J., Brunsch, R., Rogga, S., and Scholz, R. W. (2022). Perceived risks and vulnerabilities of employing digitalization and digital data in agriculture – socially robust orientations from a transdisciplinary process. *J. Clean. Prod.* 358, 132034. doi:10. 1016/j.jclepro.2022.132034