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TAM-Based Study of Farmers' Live Streaming E-Commerce Adoption Intentions

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Abstract: Amidst the digital economy surge, live streaming e-commerce of agricultural products has significantly boosted agricultural prosperity. Investigating farmers' behavioral intentions toward adopting live streaming e-commerce holds critical importance for fostering agricultural healthy and swift growth. Utilizing the Technology Acceptance Model (TAM) as a foundation, this study incorporates three additional variables—government support, platform support, and social learning—to devise a theoretical model. It takes the agriculture-related live streaming e-commerce platform as an example, with 424 Chinese farmers as the sample, to quantitatively assess the factors that impact the intentions to adopt live streaming e-commerce behaviors. The findings indicate that, firstly, the TAM is applicable to the assessment of farmers' intentions to adopt live streaming e-commerce. Secondly, government support positively impacts perceived usefulness, social learning enhances perceived ease of use, and platform support positively impacts both perceived ease of use and usefulness. Lastly, the technology acceptance extension model applicability varies among farmer groups: government support influence on perceived ease of use is more significant among traditional farmers, social learning impact on perceived ease of use is higher in farmers with higher education levels, and platform support effect on perceived usefulness is stronger among farmers experienced in e-commerce. Therefore, differentiated promotion strategies by the government are necessary, and e-commerce platforms should leverage their technology to offer efficient services and encourage farmer education. A multi-party collaboration model involving the government, platforms, and farmers is essential to collectively foster the healthy development of rural live streaming e-commerce.

Keywords: live streaming e-commerce; technology acceptance model; government support; platform support; social learning

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1. Introduction

Efficient distribution of agricultural products plays a pivotal role in agricultural operations, serving as a critical component of the agricultural value chain that directly influences farmers' income and market stability. With the advent of e-commerce, agricultural e-commerce has forged new sales avenues for farmers, effectively mitigating the challenges of information asymmetry and market volatility in traditional sales channels [1,2]. The advent of live streaming e-commerce has revitalized the distribution and sale of agricultural products within the agricultural value chain through its distinctive real-time interactive and dynamic display features [3]. Real-time live video broadcasts vividly showcase the growth, picking, and processing of agricultural products to consumers, incorporating explanations, demonstrations, and interactions, significantly enhancing the purchasing experience. This not only facilitates a more efficient value transformation for agricultural products in the value chain, but also strengthens consumer connections and supports the sustainable development and modernization of agriculture [4]. In comparison with traditional e-commerce, live streaming e-commerce has significant advantages in attracting consumers' attention, accurately matching market demand and providing a realistic and credible product display environment [5,6]. This emerging technology enables farmers to capture market changes more accurately and flexibly adjust their sales strategies, thereby improving the market adaptability and overall operational efficiency of agricultural products [7].

However, while consumers continue to be enthusiastic about purchasing agricultural products on live streaming e-commerce platforms, attracted by their fresh and intuitive displays, and enjoy a seamless field-to-table shopping experience, unexpectedly, farmers' motivation to adopt the emerging technology of live streaming e-commerce is not as strong. They appear to be relatively cautious in their approach to this emerging technology that can break traditional sales restrictions and expand market paths [8,9]. This has, to some extent, created a gap between the supply and demand sides of the market. It also raises a series of important questions: why do some farmers show strong intentions to adopt live streaming e-commerce when faced with this emerging technology, while others appear to be less motivated? What are the key factors influencing farmers' intentions to adopt live streaming e-commerce? And how do these factors interact with each other to impact farmers' decision-making process? To answer these questions, it is necessary to deeply analyze the behavioral patterns of farmers. Only by truly grasping the logic of thinking and behavioral patterns of farmers in the decision-making process can we put forward reasonable suggestions to encourage farmers to actively adopt new technologies.

With respect to the study of e-commerce platform adoption behavior, the Technology Acceptance Model (TAM) is an analytical framework that has been recognized and widely used by many scholars [10,11]. This model, which focuses on the user perspective, provides insights into the perceived usefulness and ease of use from the perspective of the users when they confront new technologies and how these perceptions further shape their attitudinal dispositions [12,13]. It provides not only a powerful tool for understanding consumers' e-commerce adoption behavior, but also lays a theoretical foundation for exploring the behavioral patterns of other user groups, such as farmers, on e-commerce platforms. Although academics have conducted numerous studies on live streaming e-commerce adoption behavior around the consumer perspective—exploring topics such as how live streaming e-commerce for agricultural products impacts consumers' purchasing decisions and consumers' shopping behavior on live streaming platforms [14–17]—there is less existing literature on farmer-level research. The adoption behavior of the farmer, as an important participant in live streaming e-commerce of agricultural products, also has a profound impact on the development of live streaming e-commerce. Therefore, applying the TAM to farmer-level research to explore the perception, attitude, and adoption behavior of farmers in the face of live streaming e-commerce technology is undoubtedly a research direction worthy of in-depth exploration.

It is equally important to explore the external impacts on the TAM. First, government support plays an important role in farmers' adoption of live streaming e-commerce. In China, the government vigorously promotes the strategy of e-commerce to promote agriculture, not only formulating a series of relevant policies to promote the development of live streaming e-commerce for agricultural products, but also actively guiding and encouraging third-party e-commerce enterprises to set up live streaming e-commerce service platforms. This move aims to enhance farmers' ability to use live streaming e-commerce for product sales and promote the modernization of agricultural product distribution [18,19]. Second, as major players in China's e-commerce market, platform companies such as TikTok e-commerce, Kuaishou e-commerce, Taobao Live, and Jingdong Live are also actively involved in providing farmers with diversified support. These supports cover a wide range of aspects such as training, technical support, product promotion, and financial assistance, aiming to attract more farmers to the e-commerce platforms [20]. In addition, farmers in rural communities are not only "economic beings" pursuing economic benefits, but also "social beings" integrating into social relationships. They tend to choose imitation and following existing strategies to reduce potential risks. In the decision to adopt the new technology of live streaming e-commerce, farmers are not only impacted by their internal factors, but also acquire knowledge and experience through communication and learning from the social environment in which they live, leading to consistent behavior [21]. However, existing literature fails to explore the process of farmers' acceptance of live streaming e-commerce as a technology in terms of external factors such as government support, platform support, and social learning. Therefore, this study is based on the TAM, and these three external impact factors are specifically selected to construct a live streaming e-commerce adoption behavioral intention model. Through the example of agriculture-related live streaming e-commerce platforms, questionnaire survey data from 424 farmers in China are utilized to quantitatively measure the path impact among the latent variables. This study aims to provide a more comprehensive understanding of the influencing factors and decision-making process of farmers in adopting live streaming e-commerce technologies and offer targeted recommendations for policymakers and e-commerce platforms to further promote the healthy development of rural e-commerce.

2. Literature Review and Research Hypotheses

2.1. Technology Acceptance Model (TAM)

TAM, proposed by Davis et al. [22], has had a profound impact on both academia and industry. Using the Theory of Reasoned Action (TRC) as a cornerstone, the model explores the mind journey of how users accept new technologies. In this model, behavioral intention is regarded as the core force that drives individual behavior, and the user's attitude toward the new technology is a key factor in shaping behavioral intention [23,24]. Such attitudes do not arise out of thin air, but are based on two core user perceptions of the technology: perceived usefulness and perceived ease of use [25].

Perceived usefulness refers to the extent to which users perceive technology as being able to improve the efficiency of their work or life. In the fast-paced, high-efficiency modern society, users favor technologies that bring practical benefits. Perceived ease of use focuses on how convenient the user feels when using the technology. Even if a technology is powerful, if it is complicated to operate and difficult to master, it will struggle to gain the users' favor [26,27]. It is particularly noteworthy that perceived usefulness not only shapes attitudes, but also directly generates behavioral intentions. This means that even if a technology does not stand out in terms of ease of use, a strong intention to use it may arise as long as the user perceives it as useful [10,28]. TAM has been widely praised for its maturity and flexibility, as researchers can adapt and expand the model's external variables based on specific research contexts and needs [29]. This underscores its utility as a robust tool for the in-depth exploration of user acceptance of new technologies, particularly in the domains of agriculture and e-commerce [30–32]. Rezaei-Moghaddam and Salehi [33] investigated the adoption intentions and attitudes of Iranian agricultural specialists toward precision agriculture technologies, revealing that the attitude toward use significantly shapes adoption intentions, while the perceived ease of use and usefulness of the technology indirectly influence adoption intentions. Mohr and Kühl [34] highlighted that the acceptance of farmers is crucial to the economic and ecological benefits of artificial intelligence systems in agriculture. They further established that personal attitudes significantly impact the adoption of such systems by agricultural workers. The study by Zarei et al. [35] also confirms that perceived ease of use and perceived usefulness are crucial factors in farmers' adoption of e-commerce platforms for selling agricultural products.

For farmers, live streaming e-commerce is a new technology that enables product display, interaction, and sales through live video streaming in an Internet virtual environment. In the process of accepting live streaming e-commerce, farmers follow the logical chain of "perception–attitude–action". Accordingly, this study will use TAM as the basis to construct an analytical framework and propose the following series of research hypotheses:

Hypothesis 1 (H1). *Attitude positively impacts the intention to adopt live streaming e-commerce.*

Hypothesis 2 (H2). *Perceived usefulness has a positive impact on the intention to adopt live streaming e-commerce.*

Hypothesis 3 (H3). *Perceived usefulness has a positive impact on attitude.*

Hypothesis 4 (H4). *Perceived ease of use has a positive impact on attitude.*

Hypothesis 5 (H5). *Perceived ease of use has a positive impact on perceived usefulness.*

2.2. Government Support

Government support usually refers to the favorable conditions and assistance provided by the government to a particular field or group at various levels, such as policy, funding, and law, to promote its healthy, orderly, and rapid development. This support can be direct financial subsidies, tax concessions, infrastructure construction, indirect regulation making, environmental optimization, etc. [36,37]. Diffusion of Innovations Theory (DIT) posits that government support is pivotal for the diffusion and adoption of new technologies or innovations. In this process, government support not only accelerates the diffusion pace, but also broadens the impact of these technologies within the social system [38–40]. Current research shows that the support provided by the government can significantly impact users' decisions on the adoption of new technologies. For example, a study by Chatterjee et al. [41] found that higher levels of government support helped strengthen users' intentions to use new technologies for vocational education and training. Jain et al. [42] showed that the level of government support is an important indicator of users' acceptance of new technology: the stronger the government support is perceived to be by the users, the greater the likelihood that they will use electric vehicles. Soe [43] studied consumers' intention to adopt e-wallet services during the COVID-19 epidemic and found that government support can influence consumers' intentions to use e-wallets by increasing perceived ease of use and perceived usefulness. Chen et al. [44] confirmed that both investment subsidies and usage subsidies provided by the government are effective in incentivizing new technology companies to increase their investments in infrastructure, in turn promoting the widespread use and diffusion of new technologies in the market. Similarly, live streaming e-commerce, as a new technology, is more likely to make farmers feel the usefulness and ease of use of live streaming e-commerce through the government multi-faceted support. Specifically, through financial subsidies and training guidance, the government can effectively reduce the technical and economic barriers encountered by farmers in the field of live streaming e-commerce, so that they feel that this technology is "easier to use". At the same time, government active publicity and market expansion strategies have enabled farmers to deeply experience the great potential of live streaming e-commerce in expanding sale paths and enhancing brand impact, thus increasing their perception of the "usefulness" of live streaming e-commerce. Accordingly, the following hypotheses are proposed:

Hypothesis 6 (H6). *Government support has a positive impact on perceived ease of use.*

Hypothesis 7 (H7). *Government support has a positive impact on perceived usefulness.*

2.3. Platform Support

In the Information System Success Model (ISSM), system quality emerges as a pivotal factor for evaluating information system success [45]. Within this context, platform support, a crucial aspect of system quality, plays a vital role in ensuring the success of an information system [46]. Driven by the Chinese government rural revitalization strategy, live streaming e-commerce platforms, such as TikTok e-commerce, Kuaishou e-commerce, Taobao Live, and Jingdong Live, have supported farmers through diversified approaches. These include, but are not limited to, training, traffic support, technical support, promotion, and financial assistance. The support of farmers by live streaming e-commerce platforms is a win-win process. By providing support measures, the platform attracts more farmers to the platform and increases the platform user activity and participation while also helping farmers to improve their own e-commerce operation capabilities, expand product awareness and sales, and achieve better economic benefits [47,48]. The existing study also points out that training, extension, technical support, and financial assistance can be used as external variables to influence the technology acceptance process directly [49]. For example, Han and Li [50] study shows that e-commerce platforms support farmers mainly in two major aspects: training support and operation support. Training support covers e-commerce talent training and e-commerce knowledge teaching, aiming to lower the threshold for farmers to use new technologies. Operation support, on the other hand, focuses more on providing financial and promotional support to farmers, ensuring that they receive the necessary financial and resource support in the process of e-commerce entrepreneurship. The research data from Shanxi Province confirms that these two types of support have a significant positive impact on farmers' intentions to adopt e-commerce technology for entrepreneurship. Takahashi et al. [51] point out that, in developing countries, farmers are facing a series of challenges, including backward technology, poor information, etc., and training is a way of transferring knowledge through which farmers in developing countries can obtain detailed information about new technologies and detailed information and operation skills so that they can be better applied to agricultural production. Liu et al. [52] identify farmers' intentions to use e-commerce technologies to sell agricultural products based on survey data from 762 farmers in Hunan Province, China, and the results of the study show that training and financial support are positively correlated with farmers' intentions to adopt e-commerce technologies. In summary, we believe that the platform provides training and technical support that could help improve farmers' perceived ease of use of live streaming e-commerce and reduce the difficulty of operation so that farmers are more willing to try it and use it. Meanwhile, e-commerce traffic support, financial support, and promotional measures help enhance farmers' perceived usefulness of live streaming e-commerce, increase farmers' recognition of live streaming e-commerce, and further promote their adoption intentions and behavior. Accordingly, the following hypotheses are proposed:

Hypothesis 8 (H8). *Platform support has a positive impact on perceived ease of use.*

Hypothesis 9 (H9). *Platform support has a positive impact on perceived usefulness.*

2.4. Social Learning

Social Learning Theory (SLT) focuses on the important role of observational learning in human behavior [53,54]. This theory focuses on the interaction between human behavior and the surrounding environment, and it is concerned with how people learn by observing and imitating the behavior of others [55,56]. In SLT, human behavior is influenced not only by one's own intrinsic motivations and needs, but also by exemplars and situational factors in the external environment. By observing the behaviors and outcomes of others, people can acquire new behavioral patterns and coping strategies to adjust their behaviors to different environmental and social requirements [57–59]. Existing research also confirms that farmers' decisions to adopt new technologies are influenced not only by their own factors but also by the social environment in which they live. Through social learning, farmers are able to acquire knowledge, enhance their experience, and ultimately demonstrate consistent behavior. For example, Conley and Christopher [60], who viewed villages as learning units involved in a collective experimentation process, found that each farmer observes the agricultural activities of other farmers, including trials of new technologies. Farmers used this information to update their perceptions of the technology and decide on the next season planting. Genius et al. [61] found social learning to be an important determinant of the adoption and diffusion of new technologies through an analysis of data from olive farms on the island of Crete, Greece. A study by Gerba et al. [62] pointed out that farmers share and acquire knowledge among themselves through communication, observation, and participation in socio-cultural activities, thus promoting the adoption of agricultural technologies. Ding et al. [63] emphasized that farmers in the process of social learning are not only confined to communication among neighbors, but also proactively seek to interact with various aspects, such as e-commerce extension workers and mass media, in order to thereby expand their knowledge and skills. This diversified learning approach enables farmers to understand and master new technologies more comprehensively, further promoting their practical application in agricultural production. Combining the above scholars' studies, we believe that social learning also plays a key role in the process of farmers adopting the new technology of live streaming e-commerce. By observing and imitating the successful experiences of others, farmers can more intuitively understand the operational skills and advantages of live streaming e-commerce, thus enhancing the perceived ease of use of live streaming e-commerce. At the same time, social learning also helps farmers recognize the value of live streaming e-commerce in the sale of agricultural products and enhances their trust in live streaming e-commerce, in turn increasing perceived usefulness. Accordingly, the following hypotheses are proposed:

Hypothesis 10 (H10). *Social learning has a positive impact on perceived ease of use.*

Hypothesis 11 (H11). *Social learning has a positive impact on perceived usefulness.*

To sum up, this study builds a behavioral intention model of live streaming e-commerce adoption by farmers based on extended TAM, as shown in Figure 1.

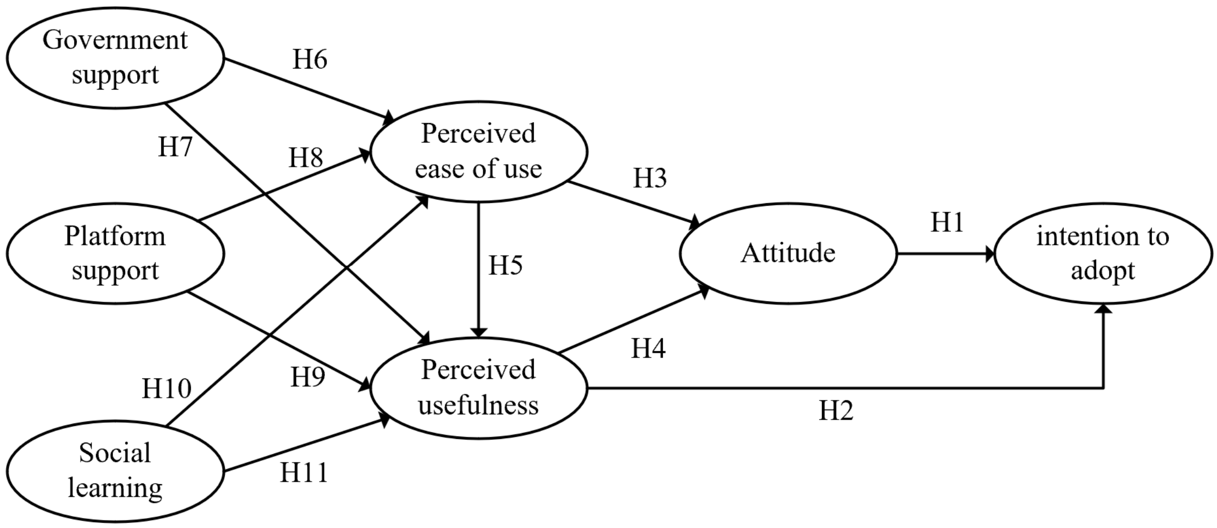

Figure 1. Research model.

3. Research Design

3.1. Data Collection

The quality of the sample is crucial to the results of the study, so the selection of the sample must be scientifically rigorous to ensure the accuracy and reliability of the results. This study adopted a rigorous questionnaire research method to collect data. Before the formal research, we combed in depth through the relevant literature and selected measurement indicators that have been verified by several scholars and have a high degree of reliability and validity. At the same time, we consulted two professors in the field of e-commerce for their professional opinions and made adjustments to the measurement indicators. In order to further ensure the adaptability of the questionnaire, we selected 10 farmers in Fujian Province for face-to-face pre-testing, discussed in depth the formulation of the questionnaire with them, and, based on their feedback, we made localized modifications to the diction of the questionnaire. It is worth noting that the pre-test data from these 10 farmers were not counted in the final analysis. After the pre-survey, we carefully designed the official questionnaire and distributed it on a large scale, specifically using a combination of online and offline methods to carry out the research, with the offline approach mainly relying on the research team members visiting local farmers and distributing the questionnaires in person, and the online approach mainly relying on the use of the online questionnaire survey platform through the paid questionnaire to the target group. The research extended from the end of September to the beginning of December 2023 and lasted more than 2 months. A total of 491 questionnaires were distributed. Following exclusion of invalid questionnaires with missing data or the same score for all questions, as well as questionnaires that had been filled in in too short a time, we finally recovered 424 valid questionnaires, with an effective recovery rate of 86.4%.

As shown in Table 1, in terms of the gender of the respondents, there were 227 male respondents, accounting for 53.5%, which was slightly higher than that of female respondents. The type of farmer representing the respondents was categorized as either traditional or new agricultural business entities according to the "Plan for High-Quality Development of New Agricultural Businesses Entities and Service Entities" published by the Chinese government. Here, the traditional agricultural business entities refer to the individual farmers, while the new agricultural business entities include family farms, large specialized households, farmers' cooperatives, and agricultural enterprises in four subcategories, with new agricultural business entities having obvious advantages in terms of business scale, technical equipment, and market status relative to traditional agricultural business entities. In the sample, new agricultural business entities accounted for 51.2%, and traditional agricultural business entities accounted for 48.8%, a comparable proportion of both which, to a certain extent, avoids the one-sidedness of the survey conclusions. In terms of the education of the respondents, high school or polytechnic school accounted for 31.8%, followed by junior high school which accounted for 27.8%; the majority of the respondents were farmers with a low level of education, a phenomenon which is in line with the typical characteristics of the farmers group. In terms of the respondents' age, 36–50 years old accounted for the highest proportion, while 50 years old and above accounted for the smallest. Finally, 61.1% of respondents said they had no experience of e-commerce, in line, to some extent, with the status quo in some regions of China, where the popularity of e-commerce in rural areas is still limited.

Table 1. Descriptive analysis of respondents.

Sample	Category	Number	Percentage (%)
Sex	Male	227	53.5
	Female	197	46.5
Type	New agricultural businesses entity	217	51.2
	Family farm	109	25.7
	Large specialized household	54	12.7
	Farmers' cooperative	46	10.8
	Agricultural enterprise	8	1.9
	Traditional agricultural business entity	207	48.8
Education	Junior high school and below	115	27.1
	High school or polytechnic school	135	31.8
	Junior college	83	19.6
	Bachelor degree and above	91	21.5
Age	18–25	119	28.1
	26–35	114	26.9
	36–50	148	34.9
	51 and above	43	10.1
E-commerce experience	Yes	165	38.9
	No	259	61.1

3.2. Variable Measurement

In this study, we used the well-known Likert seven-point scale to assess the respondents, where 1 means "extremely disagree" and 7 means "extremely agree". The higher the score, the more the respondent agrees with the question. We selected the validated high reliability and high validity scales, and scientifically revised some of the measurement items based on experts' suggestions to enhance their rigor. The measure of intention to adopt live streaming e-commerce draws on the studies of Ariansyah et al. [64] and Gao and Sheng [65], with three question items. The assessment of perceived usefulness, perceived ease of use, and attitude draws on studies by Pavlou and A [66], Huang and Yen-Ping [67], and Mullins and Cronan [68], with a total of 12 items. The measurement of government support draws on Feng et al. [69]'s study with five items. The assessment of platform support draws on Han and Li [50] study with five items. The measure of social learning is revised based on the findings in Barham et al. [70] and Crane-Droesch [71], totaling five items. The scale is detailed in Appendix A.

3.3. Research Methods

In this study, we meticulously selected the research methodology to align with the specific problem being investigated. By employing two pieces of advanced statistical analysis software, AMOS 24.0 and SPSS 24.0, we conducted several rigorous statistical analyses, including reliability, validity, and model fit tests, on meticulously screened data. With the high quality of the sample data assured, we further employed structural equation modeling to deeply explore the data to validate the 11 central hypotheses posited in this research. Additionally, we assessed model applicability across various contexts using multiple-group analysis to guarantee the comprehensiveness and practical relevance of the study. By integrating data analysis results with pertinent theories, we conducted an in-depth exploration of the relationships among variables and derived scientifically rigorous conclusions.

4. Results Analysis

4.1. Reliability Analysis

The reliability analysis helps to ensure the reliability and reproducibility of the research results, and, in this study, Corrected Item-Total Correlation (CITC), Cronbach's alpha coefficients, and Cronbach's alpha coefficient if item deleted were chosen as the evaluating indicators for measuring the reliability of the scale. The SPSS 24.0 was used for calculation, with the results shown in Table 2. The lowest CITC value of the scale question items is 0.731, surpassing the threshold of 0.5 [72], while the Cronbach's alpha coefficient values of each variable of the scale are above 0.8, and there is no significant increase in Cronbach's alpha coefficient if item deleted, indicating that the measurement of the scale does not require item deletion [73]. Overall, the reliability of the scales was satisfactory.

Table 2. Results of reliability test.

Construct	Items	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted	Cronbach's Alpha
Intention to adopt	ITA1	0.81	0.844	0.895
	ITA2	0.786	0.848	
	ITA3	0.786	0.819	
Attitude	AT1	0.768	0.844	0.885
	AT2	0.764	0.848	
	AT3	0.796	0.819	
Perceived usefulness	PU1	0.814	0.864	0.903
	PU2	0.807	0.867	
	PU3	0.731	0.894	
	PU4	0.78	0.876	

Table 2. *Cont.*

Construct	Items	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted	Cronbach's Alpha
Perceived ease of use	PEU1	0.819	0.882	0.914
	PEU2	0.783	0.895	
	PEU3	0.78	0.896	
	PEU4	0.832	0.877	
Government support	GS1	0.864	0.943	0.953
	GS2	0.881	0.94	
	GS3	0.854	0.945	
	GS4	0.882	0.94	
	GS5	0.871	0.942	
Platform support	PS1	0.878	0.934	0.949
	PS2	0.865	0.936	
	PS3	0.862	0.936	
	PS4	0.854	0.938	
	PS5	0.839	0.941	
Social learning	SL1	0.830	0.914	0.932
	SL2	0.867	0.902	
	SL3	0.841	0.910	
	SL4	0.819	0.917	

4.2. Exploratory Factor Analysis

Exploratory factor analysis is mainly used to explore the characteristics, properties, and explanatory power of variables, and is an important part of evaluating the quality of a scale. First, we calculated the KMO of the data and conducted the Bartlett's test for the significance of the data using SPSS 24.0, with the results shown in Table 3. The KMO values of the variables reside in the range of 0.744–0.917, and the Bartlett's sphere tests are all significant, indicating that the data are suitable for factor analysis [74,75]. We conducted an exploratory factor analysis and, by observing the data outputs in Table 3, it can be seen that the commonalities of all the question items are greater than 0.5 and the factor loadings are all greater than 0.6, meeting the recommended values [76]. Only one factor with an eigen value greater than 1 could be rotated for each variable, and the cumulative variances are all higher than 50%, indicating that the analyzed factors in this study were able to provide a better explanation for each variable.

Table 3. Results of exploratory factor analysis.

Construct	Items	KMO	Bartlett's Sphere Test	Commonality	Factor Loading	Eigenvalue	Total Variation Explained
Intention to adopt	ITA1	0.75	0	0.842	0.918	2.482	82.72
	ITA2			0.82	0.905		
	ITA3			0.82	0.905		
Attitude	AT1	0.744	0	0.806	0.898	2.439	81.306
	AT2			0.801	0.895		
	AT3			0.833	0.913		
Perceived usefulness	PU1	0.846	0	0.811	0.901	3.103	77.58
	PU2			0.804	0.896		
	PU3			0.714	0.845		
	PU4			0.774	0.88		
Perceived ease of use	PEU1	0.852	0	0.814	0.902	3.18	79.498
	PEU2			0.772	0.879		
	PEU3			0.767	0.876		
	PEU4			0.827	0.91		

Table 3. *Cont.*

Construct	Items	KMO	Bartlett's Sphere Test	Commonality	Factor Loading	Eigenvalue	Total Variation Explained
Government support	GS1 GS2 GS3 GS4 GS5	0.913	0	0.835 0.857 0.822 0.857 0.844	0.914 0.926 0.906 0.926 0.918	4.215	84.292
Platform support	PS1 PS2 PS3 PS4 PS5	0.917	0	0.854 0.839 0.835 0.825 0.805	0.924 0.916 0.914 0.908 0.897	4.157	83.143
Social learning	SL1 SL2 SL3 SL4	0.861	0	0.819 0.861 0.833 0.807	0.905 0.928 0.913 0.898	3.319	82.985

4.3. Confirmatory Factor Analysis

Factor analysis can be used to test whether the measurement model or theoretical construct proposed by the researcher fits the actual data. Squared Multiple Correlation (SMC), factor loading, Average Variances Extracted (AVE), and Composite Reliability (CR) are some of the common indicators, with the SMC value required to be greater than 0.4 [72], the factor loading required to be greater than 0.6, the AVE value required to be greater than 0.5, and the CR value required to be greater than 0.7 [77]. We first measured the SMC and factor loadings by IBM AMOS 24.0; the results are shown in Table 4. The lowest SMC value in the scale question item is 0.608, and the lowest factor loading is 0.780, in line with the criteria of the recommended values. Then, we calculated the AVE and CR values based on the factor loadings, where the lowest AVE value was 0.703 and the lowest CR value was 0.885, both of which were higher than the minimum standard values proposed by scholars. Therefore, it can be determined that the scale has good convergent validity and composite reliability.

Discriminant validity is one of the important criteria for assessing the quality of measurement tools and validating theoretical models, as it is able to determine whether the variables uniquely represent a different concept or dimension. In this study, two methods, the Fornell–Larcker criterion and the Heterotrait–Monotrait ratio (HTMT), were used to assess the discriminant validity among the variables. According to the suggestion by Fornell and Larcker [78], if the square root value of AVE is greater than the correlation coefficient between any two variables, the scale has good discriminant validity. As shown in Table 5, the two-by-two correlation coefficients among the main variables in this study are lower than the square root value of AVE, meeting the criteria proposed by Fornell and Larcker. Second, we calculated the HTMT values by comparing the correlation coefficients among different variables (Heterotrait) with the correlation coefficients within the same variable (Monotrait). According to the suggestions by Awang [79] and Hair Jr. et al. [80], if the HTMT values are below a certain predefined threshold (e.g., 0.85 or 0.90), it can be considered that they have good discriminant validity among different variables. As all the values in Table 6 are below 0.85, the scale can be considered to have passed the test of discriminant validity.

Table 4. Results of convergent validity.

Construct	Items	Factor Loading	SMC	AVE	CR
Intention to adopt	ITA1	0.872	0.760	0.741	0.896
	ITA2	0.848	0.719		
	ITA3	0.862	0.743		
Attitude	AT1	0.841	0.707	0.72	0.885
	AT2	0.841	0.707		
	AT3	0.864	0.746		
Perceived usefulness	PU1	0.874	0.764	0.703	0.904
	PU2	0.860	0.740		
	PU3	0.780	0.608		
	PU4	0.837	0.701		
Perceived ease of use	PEU1	0.869	0.755	0.728	0.915
	PEU2	0.838	0.702		
	PEU3	0.825	0.681		
	PEU4	0.880	0.774		
Government support	GS1	0.889	0.790	0.803	0.953
	GS2	0.904	0.817		
	GS3	0.877	0.769		
	GS4	0.913	0.834		
	GS5	0.898	0.806		
Platform support	PS1	0.914	0.835	0.789	0.949
	PS2	0.897	0.805		
	PS3	0.883	0.780		
	PS4	0.882	0.778		
	PS5	0.864	0.746		
Social learning	SL1	0.874	0.764	0.774	0.932
	SL2	0.907	0.823		
	SL3	0.878	0.771		
	SL4	0.860	0.740		

Table 5. Discriminant validity: Fornell–Larcker criterion.

	ITA	AT	PU	PEU	GS	PS	SL
ITA	**0.861**						
AT	0.798	**0.849**					
PU	0.828	0.825	**0.838**				
PEU	0.664	0.717	0.729	**0.853**			
GS	0.519	0.510	0.627	0.617	**0.896**		
PS	0.605	0.617	0.669	0.678	0.770	**0.888**	
SL	0.564	0.551	0.570	0.739	0.601	0.664	**0.880**

Note: The diagonal of the matrix (boldface) is the square root of AVE.

Table 6. Discriminant validity: Heterotrait–Monotrait ratio (HTMT).

	ITA	AT	PU	PEU	GS	PS	SL
ITA							
AT	0.800						
PU	0.828	0.830					
PEU	0.664	0.719	0.730				
GS	0.521	0.511	0.627	0.616			
PS	0.604	0.618	0.668	0.677	0.768		
SL	0.570	0.554	0.579	0.746	0.603	0.660	

4.4. Model Fitting

In structural equation modeling, a fit indicator is mainly used to assess the degree of fit between the theoretical model and the actual data, with common indicators including chi-squared test of independence, RMSEA, SRMR, etc., all of which usually have certain thresholds for judging the degree of fit. Whittaker and Schumacker [81] and Kline and Santor [82] suggest that the RMSEA and SRMR must be less than 0.08, while GFI, NFI, TLI, and CFI must be greater than 0.9. As it can be seen from Table 7, all the indicators are within the range of the thresholds, indicating that the model has a good fit with respect to the data [83].

Table 7. Adaptability of SEM.

Common Indices	χ^2/df	RMSEA	GFI	NFI	TLI	CFI	SRMR
Judgment criteria	<5	<0.08	>0.9	>0.9	>0.9	>0.9	<0.08
CFA Value	1.711	0.041	0.910	0.951	0.977	0.979	0.028

4.5. Hypothesis Test

In this study, we applied structural equation modeling for path analysis and validated the proposed hypotheses. Figure 2 demonstrates the specific results of the model path analysis. In addition, we obtained the results of the regression coefficients of the structural equation modeling, and the detailed data can be seen in Table 8. First, we validated TAM, with the results showing that attitude significantly and positively impacted intention to adopt live streaming e-commerce ($\beta = 0.411$, $p < 0.001$); therefore, H1 holds. Perceived usefulness significantly and positively impacted intention to adopt live streaming e-commerce ($\beta = 0.570$, $p < 0.001$); therefore, H2 holds. Both perceived ease of use and perceived usefulness were found to be able to significantly and positively affect attitudes, and the impact of perceived usefulness on attitudes was found to be greater ($\beta = 0.219$, $p < 0.001$; $\beta = 0.607$, $p < 0.001$); therefore, H3 and H4 hold. Perceived ease of use significantly and positively affected perceived usefulness ($\beta = 0.470$, $p < 0.001$); therefore, H5 holds. Thus, TAM provides an effective analytical framework when considering farmers' intentions to adopt live streaming e-commerce.

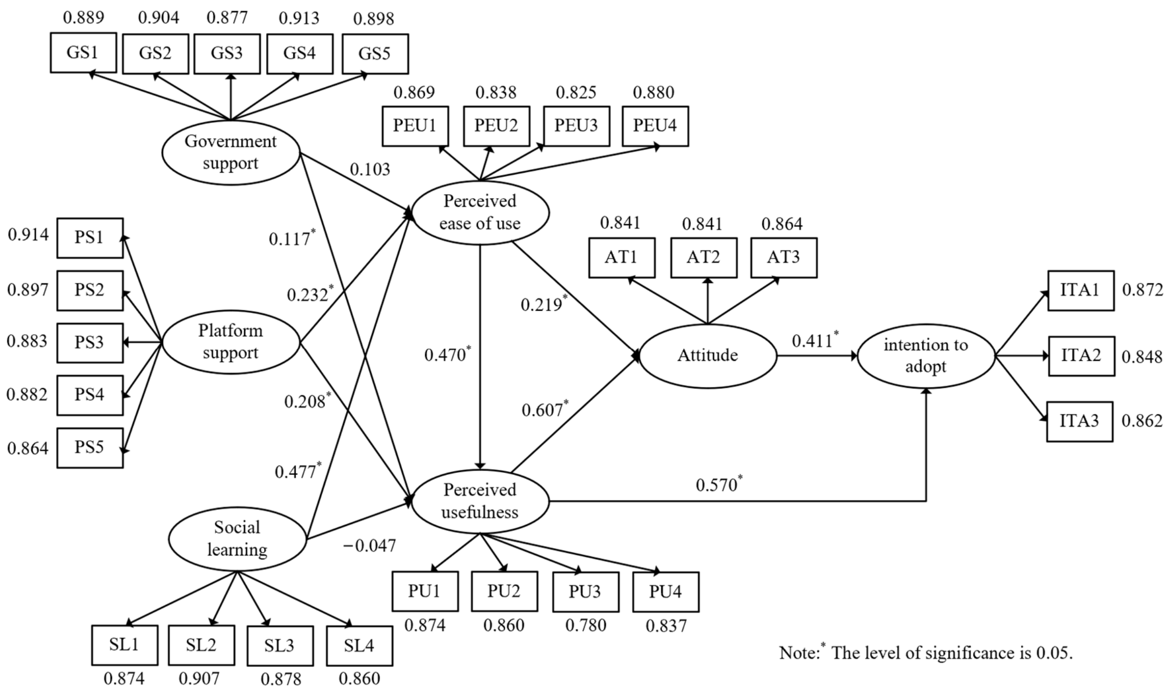

Figure 2. Analysis results of the hypothesized model.

Table 8. Results of the path analysis test.

Hypothesis	Path	Estimate	S.E.	C.R.	VIF	*p*-Value	Results
H1	AT → ITA	0.411	0.083	4.956	2.225	0	Support
H2	PU → ITA	0.570	0.079	7.172	2.225	0	Support
H3	PU → AT	0.607	0.059	10.33	1.791	0	Support
H4	PEU → AT	0.219	0.049	4.448	1.791	0	Support
H5	PEU → PU	0.470	0.062	7.576	2.217	0	Support
H6	GS → PEU	0.103	0.053	1.960	2.255	0.051	No Support
H7	GS → PU	0.117	0.050	2.369	2.294	0.018	Support
H8	PS → PEU	0.232	0.058	3.963	2.489	0	Support
H9	PS → PU	0.208	0.056	3.694	2.627	0	Support
H10	SL → PEU	0.477	0.052	9.255	1.710	0	Support
H11	SL → PU	−0.047	0.055	−0.864	2.174	0.388	No Support

Second, we examined the impacts of government support, platform support, and social learning on the TAM, with the results showing that platform support significantly and positively affected perceived ease of use and perceived usefulness ($\beta = 0.232$, $p < 0.001$; $\beta = 0.208$, $p < 0.001$); therefore, H8 and H9 hold, suggesting that platform support affects the adoption of live streaming e-commerce by farmers and is a significant external factor with respect to this new technology. However, government support only significantly and positively affected perceived usefulness ($\beta = 0.117$, $p < 0.05$), having a non-significant effect on perceived ease of use ($\beta = 0.103$, $p > 0.05$). Therefore, H7 holds, but H6 does not. Interestingly, social learning had a non-significant effect on perceived usefulness ($\beta = -0.047$, $p > 0.05$), but a significant positive effect on perceived ease of use ($\beta = 0.477$, $p < 0.001$); therefore, H10 holds, while H11 does not. As mentioned before, perceived usefulness and perceived ease of use are two different concepts; therefore, the variables affecting them are not the same, which may be due to factors such as their perceptions, expectations, and operational experience of live streaming e-commerce. Meanwhile, the Variance Inflation Factor (VIF) of all paths was found to be between 1–3, which is less than the critical value of 5 [80], indicating that there is no serious multicollinearity problem among the variables of the research model.

4.6. Moderating Effect Analysis

Although we tested the antecedents of farmers' intentions to adopt live streaming e-commerce through structural equation modeling, the relationship between them may be affected by a variety of factors. Testing the moderating effects helps the researchers gain a deeper understanding of the relationship among the variables and further explore the changes in these relationships across different contexts. Therefore, we introduced three moderator variables, i.e., type of farmer, education, and e-commerce use experience, all three of which are dichotomous variables. The farmer type is divided into traditional agricultural business entity and new agricultural business entity. Junior high school and below, high school, or polytechnic school are included in the low education, junior college, bachelor's degree, and above are included in the high education group. E-commerce experience is divided into two groups based on the yes and no of e-commerce use experience. Results for the comparison of whether there is a significant difference between the hypothetical model and the original model to determine whether the moderating effect exists or not are shown in Table 9. The type of farmer was found to moderate the impact of government support on perceived usefulness (CMIN = 6.737, $p < 0.01$). The level of education was found to moderate the impact of perceived ease of use on attitude (CMIN = 5.155, $p < 0.05$) and also the impact of social learning on perceived ease of use (CMIN = 6.624, $p < 0.01$). Lastly, e-commerce experience was found to moderate the impact of platform support on perceived usefulness (CMIN = 4.080, $p < 0.05$).

Table 9. Results of the moderation effect.

Path	Type		Education		Experience	
	CMIN	*p*	CMIN	*p*	CMIN	*p*
AT → ITA	0.046	0.830	0.047	0.827	1.929	0.165
PU → ITA	0.262	0.609	0.154	0.694	0.424	0.515
PU → AT	0.876	0.349	1.464	0.226	2.401	0.121
PEU → AT	2.259	0.133	5.155	0.023	2.407	0.121
PEU → PU	1.559	0.212	1.437	0.231	3.833	0.051
GS → PEU	0.005	0.943	2.288	0.130	2.421	0.120
GS → PU	6.737	0.009	0.009	0.924	2.682	0.101
PS → PEU	0.081	0.777	0.004	0.948	0.304	0.581
PS → PU	0.283	0.595	0.001	0.970	4.080	0.043
SL → PEU	0.004	0.840	6.624	0.001	0.382	0.536
SL → PU	0.497	0.481	0.048	0.700	2.147	0.143

In order to further understand the direction of the moderating effect, we compared the influence paths with significant moderating effects by grouping, with the results shown in Table 10. Regarding the influence of government support on perceived usefulness, this was found to be significantly higher in the traditional agricultural business entity group than in the new agricultural business entity group, indicating that the positive impact of government support on perceived usefulness is more significant with respect to the traditional agricultural business entities. Concerning the impact of perceived ease of use on attitudes, the effect was significantly less pronounced within the high education group compared to the low education group, indicating a more substantial positive impact of perceived ease of use on attitudes among farmers with lower educational levels. Regarding the impact of social learning on perceived ease of use, this was found to be significantly higher in the high education group than in the low education group, indicating that the positive impact of social learning on perceived ease of use increases with higher levels of education. On the impact of platform support and perceived ease of use, the coefficient was found to be larger and significant in the group of farmers with e-commerce experience, while it was found to be insignificant in the group of farmers without e-commerce experience. This indicates that, even though farmers are able to access some knowledge of live streaming e-commerce through social learning, it may be difficult for them to perceive the ease of use of live streaming e-commerce if they lack practical experience of its operation.

Table 10. The comparison of path coefficients with significant moderating effects.

Moderating Variable		Path	β	*p*
type	traditional	GS → PU	0.289	0.001
	new		0.025	0.702
Education	low	PEU → AT	0.326	0.001
	high		0.110	0.057
	low	SL → PEU	0.383	0.001
	high		0.670	0.001
Experience	yes	PS → PU	0.379	0.001
	no		0.123	0.062

5. Conclusions and Future Studies

5.1. Conclusions and Discussions

Based on the technology acceptance theory, this study delves into the antecedent factors that motivate farmers to accept live streaming e-commerce and analyzes the differences in the impact of farmers' characteristics on their intentions to adopt the e-commerce technology. By empirically analyzing data from 424 farm households in China, we draw the following research conclusions.

First, TAM has applicability in the study of farmers' intentions to adopt live streaming e-commerce (Support H1–H5). The study shows that farmers' intentions to adopt live streaming e-commerce is closely related to their attitudes toward the technology. Moreover, farmers' perceived usefulness and perceived ease of use of live streaming e-commerce are factors that influence their attitude and ultimate intentions to adopt the technology. This means that, if farmers perceive live streaming e-commerce as beneficial and easy to use for marketing their agricultural products, they are more likely to adopt this new sales method, a view that supports the studies of Hoque et al. [84] and Fayad and Paper [85]. Among them, perceived usefulness has the most prominent effect in the TAM, suggesting that, when deciding whether or not to adopt live streaming e-commerce, farmers place great importance on whether this technology can bring practical benefits to their agricultural production and marketing. Therefore, when promoting live streaming e-commerce, more emphasis should be placed on communicating its practical value and economic benefits, while providing the necessary support and services to help farmers better apply this new technology.

Second, government support, platform support, and social learning are three important factors affecting TAM. Specifically, government support has a significant positive impact on perceived usefulness (Support H7), and Li, Zhen, and Zhang [8] argued that the government can provide practical help to farmers through e-commerce poverty alleviation policies, provision of financial assistance and skills training, and other initiatives, thus stimulating farmers' intentions to utilize e-commerce platforms for their entrepreneurship. The results of this study are similar to the above view, but the difference is that government support was not found to promote perceived ease of use (not supported H6), a phenomenon which may be due to a disconnect between the content of government training and the actual needs of farmers. Although the government organizes relevant skills training, the training may be too theoretical and fail to meet the specific needs of farmers, leading to difficulties in the actual operation of the farms. Platform support has a significant positive impact on both perceived ease of use and perceived usefulness (in support of H8 and H9), a result that progressively validates the findings of Han and Li [50]. Social learning has a significant positive impact on perceived ease of use (supporting H10), and this result partially supports Gerba, Leta, Till, Stellmacher, Girma, Kelboro, Kristof, Van, Assche, and Anna-Katharina [62], who argued that interactive communication among neighbors is an important way for farmers to acquire new knowledge and learn new skills, with this type of social learning playing a crucial role in farmer acceptance and adoption of new technologies. However, what makes a difference is that the impact of social learning on perceived usefulness is not significant (does not support H11), even though farmers are able to understand more intuitively the operation process and use skills of live streaming e-commerce when they are exposed to live streaming e-commerce through social learning methods such as communication among neighbors and demonstration observation, which improves their perception of live streaming e-commerce ease of use. However, social learning occurs more within farmers' social circles, and, if positive information about the usefulness of live streaming e-commerce is insufficient or poorly transmitted within farmers' social circles, then farmers may not fully recognize the practical value of live streaming e-commerce.

Finally, the applicability of the technology acceptance expansion model varies among different groups of farmers. The role of government support on perceived usefulness enhancement is more prominent among traditional agricultural business entities. A possible reason for that is that traditional farmers usually carry out agricultural production on a household basis, with a lower degree of commercialization and a lower understanding of new sales models and e-commerce platforms; therefore, government support can help traditional farmers understand the advantages of live streaming e-commerce and increase their awareness and acceptance of this new sales model. Comparatively speaking, new agricultural business entities have a higher level of agricultural production and management, and they have a certain degree of knowledge about new sales models, such as live streaming e-commerce; therefore, government support has a less obvious role in promoting perceived usefulness. The promotion impact of social learning on perceived usefulness is more obvious in the group of farmers with high education levels. It is not difficult to understand that the group with a high education level usually has stronger learning ability and comprehension abilities and is able to absorb new knowledge more quickly, thus improving the perceived ease of use. Moreover, the social circle of farmers with high education level may be more extensive and diversified, enabling them to acquire more comprehensive and in-depth technical knowledge and usage experience when learning through social learning, thus improving the perceived of ease of use. The impact of platform support on perceived usefulness is more prominent in the group of farmers with e-commerce experience, possibly because farmers with e-commerce experience already have certain e-commerce knowledge and skills, and, when they receive support from the platform, it is easier for them to combine this support with their own a priori knowledge and experience, and quickly perceive the usefulness of the support for improving business efficiency and increasing revenues.

5.2. Theoretical Contribution

This study significantly contributes to the advancement of technology acceptance theory by validating its applicability, identifying new impacting factors, and uncovering variations in its applicability. These insights not only deepen our understanding of farmers' technology adoption behaviors, but also offer fresh theoretical perspectives and avenues for future research.

Firstly, this study validates TAM applicability to the assessment of farmers' intentions to adopt live streaming e-commerce, thereby supporting the theory's relevance in niche groups and novel application domains. While conventional studies on technology acceptance have focused on enterprises and consumers, this study redirects the attention to farmers, a group with distinct characteristics and needs with respect to the adoption of information technology.

Secondly, by integrating DIT, ISSM, and SLT, this study thoroughly investigates how government support, platform support, and social learning factors impact technology acceptance, offering a novel theoretical lens for the field. This exploration of how these factors impact farmers' perceived usefulness and ease of use not only enhances comprehension of their technology adoption behaviors, but also augments the array of influencing factors within the technology acceptance model.

Finally, the discovery of variations in the technology acceptance extension model applicability among different farmer groups underscores the importance of tailoring and contextualizing the application of the theory. Future research is encouraged to delve into the characteristics and influencing factors of technology acceptance across diverse farmer groups, fostering the theory deeper evolution within the agricultural sector.

5.3. Practical Implication

The study shows that government support, e-commerce platform support, and social learning are crucial for farmers to embrace new technologies. Therefore, it is recommended that the government strengthen guidance and the e-commerce platform optimize resources while motivating farmers to promote the development of live streaming e-commerce.

First, government support has a significant impact on perceived usefulness, but not on perceived ease of use. Therefore, on the one hand, the government should formulate more specific and targeted policies for the development of e-commerce to promote agriculture, provide financial assistance and financial support, improve the construction of rural e-commerce infrastructure, and help farmers solve difficulties in terms of funding and technology. On the other hand, the skills training organized by the government should be closer to the actual needs of the farmers, and, combined with the characteristics of the local agricultural industry and the market situation, it should provide customized and practical training content to ensure that farmers can apply what they have learned.

Second, platform support has a significant impact on farmers' perceived ease of use and perceived usefulness. Therefore, live streaming e-commerce platforms should continue to improve their functions and provide more convenient and efficient services, such as one-click operation, intelligent recommendation, data analysis, etc., to reduce the difficulties encountered by farmers with respect to e-commerce use and enhance their experience. At the same time, the successful practice of live streaming e-commerce in the sale of agricultural products, brand building, and other aspects can be demonstrated by creating typical cases and setting up benchmark enterprises, providing farmers with experience and models that can be drawn on.

Third, social learning has a significant impact on farmers' perceived ease of use, but not on perceived usefulness. Therefore, farmers should continue to be encouraged to share their experiences and insights in the use of live streaming e-commerce through neighborhood communications and demonstrations to promote the effective dissemination of information within the farmers' social circle. At the same time, the organization of cross-region and cross-industry exchange activities, online communities, and other ways to help farmers expand their social circle and come into contact with more useful information and resources about live streaming e-commerce should also be encouraged.

Fourth, in the development of rural e-commerce, the government, e-commerce platforms, and farmers need to form a closely cooperative operating model, integrate the resources of all parties, utilize their respective strengths, and form a synergy. The government can, through cooperation with the e-commerce platform, transform policies into concrete action measures and ensure the implementation of policies. The e-commerce platform, on the other hand, can utilize the policy support and financial support provided by the government to further expand its business scope and improve its service quality. Farmers, with the support of the government and the platform, can better grasp market opportunities and improve their own e-commerce operation capabilities.

Finally, the applicability of the technology acceptance expansion model varies among different groups of farmers; therefore, it is necessary to develop differentiated promotion strategies for different groups of farmers. For traditional agricultural business entities, as they know less about new sales models and e-commerce platforms, guidance and support should be strengthened, and targeted training and services should be provided. With respect to new agricultural business entities, they should be encouraged to hold demonstrations, guiding other farmers through experience sharing and cooperative exchanges. For highly educated groups of farmers, the social learning impact should be strengthened, and exchange activities should be organized to promote experience sharing. For farmers with e-commerce experience, platform enterprises should provide more professional support to help them improve their business efficiency and profitability. Through these strategies, the popularization and application of live streaming e-commerce among farmers can be promoted more effectively.

5.4. Limitations and Future Studies

While this study offers valuable insights, it also presents limitations that suggest areas for future improvement. Data collection was primarily conducted through questionnaires. However, the educational, linguistic, and cognitive differences among the interviewed farmers might have influenced the accuracy of their responses. To enhance result validity in future studies, we plan to employ a combination of methods including document analysis, observation, and interviews, alongside questionnaires, for cross-validation. Awareness of potential sample bias prompts plans to refine sampling strategies in future work to ensure representativeness. The research model prioritizes the influence of government support, e-commerce platforms, and social learning on technology acceptance among farmers, deliberately excluding other variables for simplicity. Future studies should incorporate additional factors to enrich our understanding of farmers' readiness to embrace live streaming e-commerce. Moreover, the reliance on cross-sectional data at specific points in time limits the study's ability to elucidate time-dependent relationships among variables.

Future endeavors should focus on longitudinal studies to thoroughly examine variable evolution and interactions over time, aiming for a precise understanding of dynamic changes. Considering measurement scales, existing tools may not encapsulate all variable nuances, prompting future exploration of more precise and comprehensive methods.

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Appendix A. Check List of Variables Items

Construct	Items	Source
Intention to adopt	ITA1: I am willing to try to adopt live streaming e-commerce for marketing. ITA2: I will continue to pay attention to and use live streaming e-commerce to sell agricultural products in the future. ITA3: I will recommend selling agricultural products through the live streaming e-commerce model to others.	[64,65]
Attitude	AT1: It's a good idea to use live streaming e-commerce to sell products. AT2: I like the idea of using live streaming e-commerce to sell produce. AT3: There is a lot of value in using live streaming e-commerce to sell produce.	[66–68]
Perceived usefulness	PU1: I think using live streaming e-commerce can increase my income. PU2: I think the use of live streaming e-commerce can improve the efficiency of transactions. PU3: I think adopting live streaming e-commerce can reduce operating costs. PU4: I think the adoption of live streaming e-commerce is good for market expansion.	
Perceived ease of use	PEU1: It is easier to sell agricultural products using live streaming e-commerce. PEU2: It is easier to learn how to sell agricultural products using live streaming e-commerce. PEU3: It is easier to train people to use live streaming e-commerce. PEU4: It is easier to maintain live streaming e-commerce platforms (e.g., Taobao, TikTok, Kuaishou, Pinduoduo, etc.).	
Government support	GS1: The government provides policy support for farmers' live streaming e-commerce. GS2: The government organizes live streaming e-commerce training for farmers. GS3: The government provides financial subsidies for farmers to sell agricultural products through live streaming e-commerce. GS4: The government actively promotes live streaming e-commerce for farmers. GS5: The government has cooperated with live streaming e-commerce platforms.	[69]
Platform support	PS1: The platform provides training support to farmers for live streaming e-commerce. PS2: The platform provides certain network traffic support for farmers' live streaming e-commerce. PS3: The platform provides technical support for farmers' live streaming e-commerce. PS4: Platform provides regular promotion for farmers' live streaming e-commerce and products. PS5: The platform provides financial support for farmers' live streaming e-commerce.	[50]

Construct	Items	Source
Social learning	SL1: Frequency of learning about live streaming e-commerce through communication with friends and neighbors SL2: Frequency of learning about live streaming e-commerce through exchanges with big e-commerce players SL3: Frequency of learning live streaming e-commerce related knowledge through communication with e-commerce extension workers SL4: Frequency of learning about live streaming e-commerce through mass media such as the Internet, TV, radio, etc.	[70,71]

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