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Acceptance of new agricultural technology among small rural farmers

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Amid China's 2023 policy shift toward rural revitalization and agricultural modernization driven by a substantial agricultural population and the foundational role of agriculture in the national economy, there is an urgent need for the widespread adoption of new agricultural technologies to boost production quality, efficiency, and economic development. This study examines the determinants of technology adoption in agriculture among small rural farmers, focusing on the unified theory of acceptance and use of technology framework. Using a cross-sectional survey approach and a convenience sampling method, the study ultimately collected 326 responses from rural farmers. The collected data were analyzed using a structural equation modeling method with SmartPLS 4 software. The results reveal significant determinants of the intention to use new agricultural technology and the use of new agricultural technology, with performance expectancy, effort expectancy, and hedonic motivation exhibiting positive effects. Facilitating conditions have emerged as key factors influencing both the intention and usage of new agricultural technology. Although age does not moderate any of the relationships, using years moderates the relationship between performance expectancy and intention to use new agricultural technology as well as price value and intention to use new agricultural technology. Intention to use new agricultural technology has significant and positive mediating effects on the proposed relationships. The theoretical implications of this study underscore the significance of understanding the complex interplay of determinants, moderating factors, and mediating pathways within the unified theory of acceptance and use of technology framework to advance the knowledge of agricultural technology adoption. This study provides valuable perspectives for policymakers, practitioners, and researchers dedicated to promoting the adoption of sustainable technology in the agricultural sector.

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Introduction

In 2023, the Chinese government introduced a new policy focusing on the advancement and construction of rural areas. This initiative signifies a collective effort involving the entire party and society to comprehensively drive rural revitalization. The aim is to expedite the modernization of China's agricultural and rural regions, promote the development of contemporary facility-based agriculture, reinforce support for agricultural science, technology, and equipment, and fortify the construction of agricultural infrastructure (Zhang and Guo 2023).

China has a substantial agricultural sector, with the agricultural population accounting for nearly half of the total population and the value of agricultural output accounting for a significant proportion of the national economy (Liu et al. 2020). Agriculture is the cornerstone of the national economy and serves as a crucial safeguard for national security (Wang et al. 2021). As the social economy advances and science and technology progress, the agricultural production mode and production efficiency have undergone significant changes, and new agricultural technologies are constantly emerging, providing a strong impetus and support for agricultural modernization (Reddy 2019; Zhang et al. 2020; Khanh Chi, 2022; Zhang and Guo 2023). However, innovation and promotion of agricultural technology do not happen overnight, and farmers need to be the primary contributors to agricultural production to actively adopt and apply new agricultural technology to realize the quality and efficiency of agricultural production and promote the development of the agricultural economy (Zheng et al. 2022; Duncan et al. 2022).

Farmers are the key link in agricultural technology innovation and promotion, and their acceptance of new agricultural technologies directly affects their popularization and application of agricultural technologies (Reddy and Mehjabeen 2019; Guo et al. 2022; Hu et al. 2022). However, owing to the special characteristics of Chinese agriculture, the technology adoption behavior of farmers is affected by many factors, including their own characteristics, the characteristics of new agricultural technologies, and the constraints of the external environment (Guo et al. 2022). The interactions and comprehensive effects between these influencing factors determine farmers' willingness to adopt technology and their behavior (Liu et al. 2021). Therefore, an in-depth analysis of farmers' technology adoption behavior and exploration of its influencing factors and mechanisms holds immense theoretical and practical importance in fostering innovation and the dissemination of agricultural technology as well as enhancing the efficiency and quality of agricultural production.

Prior empirical inquiries into the adoption of new agricultural technology have employed diverse models, including Behavioral Reasoning Theory (Pillai and Sivathanu 2020), the Technology Acceptance Model (Duang-Ek-Anong et al. 2019), and Innovation Diffusion Theory (Mandari et al. 2017). However, there is a research gap concerning the examination of the predictors that influence the utilization of new agricultural technologies within the unified theory of acceptance and use of technology (UTAUT) framework. Despite the proven applicability of the UTAUT model in the healthcare sector (Alam et al. 2020), the agricultural sector's unique context necessitates a comprehensive model, such as the UTAUT, to elucidate present developments and contribute significantly to the existing knowledge base. Additionally, previous UTAUT-based studies, potentially because of their focus on the early stages of agricultural technology adoption, did not incorporate actual behavior. However, integrating actual behavior into the UTAUT model is imperative to obtain a comprehensive understanding of the adoption of new agricultural technology. Furthermore, the current UTAUT model does not consider price value (PV) in its framework to recognize the predictors of technology acceptance in the agricultural domain. Several studies in the agricultural domain, such as the one conducted by Shi et al. (2022), have employed the UTAUT framework. However, these studies, including Shi et al. (2022), have a notable gap in that they do not incorporate sociodemographic factors as moderation factors, and no explanations are provided for this omission. Consequently, a novel research effort employing a comprehensive framework to investigate the determining factors of the acceptance of new agricultural technology among small farmers is warranted.

Thus, this study attempts to fill the gaps in the above studies by expanding in-depth research on farmers' technology adoption behavior as well as to provide new perspectives and methods for understanding and improving farmers' technology adoption behavior using UTAUT. The significance of this study lies in its exploration of the adoption of new agricultural technologies within the UTAUT framework, which addresses a notable research gap. *First*, by integrating diverse models and considering actual behavior, this study provides valuable insights into the agricultural sector and a comprehensive foundation for predicting and promoting the acceptance of new agricultural technologies among agricultural entrepreneurs. *Second*, this research establishes the need for a nuanced approach, recognizing the impact of facilitating condition (FC), and underscores its relevance for the evolving landscape of agricultural development and technology adoption. Third, through an exploration of moderation effects, this study identifies contextual variables that may enhance or impede the relationship between key predictors and technology acceptance among agricultural entrepreneurs. This holistic approach expands the theoretical underpinnings of technology adoption in the agricultural sector and provides actionable insights for policymakers and stakeholders, facilitating the development of targeted interventions tailored to specific contextual nuances. This study contributes to the advancement of knowledge regarding agricultural technology adoption, making it particularly relevant for guiding informed decision-making and fostering sustainable agricultural development.

Literature review

Overview of new agricultural technology. In this study, the term 'new agricultural technology' primarily refers to precision agriculture technologies. Precision agriculture is a modern farming management concept that utilizes digital techniques to monitor and optimize agricultural production processes (Trivelli et al. 2019). These include advanced tools and methods such as: drones, automated tractors and satellite-guided equipment. Drones are pivotal in crop monitoring, enabling real-time assessment of crop health, disease identification, and precise application of inputs like fertilizers and pesticides (Das 2024). Automated tractors equipped with GPS and sensors optimize planting, plowing, and harvesting operations, leading to improved efficiency and reduced labor costs (Serrano et al. 2018). Satellite-guided equipment is also utilized for precision planting and irrigation, ensuring optimal application of seeds and water, resulting in better crop yields and resource conservation (Tsouros et al. 2019).

Precision agriculture has been rapidly adopted in rural areas of China, driven by government initiatives to modernize the agricultural sector and address challenges related to food security and sustainable farming practices. The implementation of precision agriculture technologies in China has enabled farmers to optimize resource utilization and improve crop yields, particularly in regions with extensive agricultural lands, leading to more efficient management practices (Kendall et al. 2017). Both public and private investments have been instrumental in supporting the development of precision agriculture in China, focusing on enhancing rural infrastructure, providing training programs for farmers, and integrating digital technologies into agriculture (Huang and Rozelle 2018). The ongoing progress of precision agriculture in rural China, primarily concentrating on staple crops like rice and wheat, is expected to further enhance agricultural productivity, mitigate environmental impacts, and elevate the livelihoods of farmers (Kendall et al. 2017). Technologies such as drones for crop monitoring, automated tractors with GPS, and satellite-guided equipment for precision planting and irrigation are pivotal in driving these positive changes in Chinese agriculture (Kendall et al. 2017).

The advancement of precision agriculture in China is rooted in technological innovations, shifting traditional farming practices towards more quantitative, localized, and technology-driven approaches (Feng 2024). This transition not only boosts agricultural productivity but also helps in reducing the negative environmental impacts associated with conventional farming practices (Kendall et al. 2017). As China continues to prioritize the development of precision agriculture, the sector is anticipated to play a crucial role in promoting sustainable agricultural practices, ensuring food security, and fostering rural development in the country.

Theoretical foundation and hypothesis development. The UTAUT aims to measure the factors influencing the acceptance and use of technology in various contexts. This model was developed by Venkatesh et al. (2003) by integrating several behavioral theories with four core and four control variables. The four core variables are social influence (SI), effort expectancy (EE), FC, and performance expectancy (PE). The four control variables are voluntariness, gender, age, and experience. The UTAUT model has been proven to be effective in evaluating the acceptance and use of technology in various studies in various contexts, including the insurance industry (de Andrés-Sánchez and Gené-Albesa 2023), digital library applications (Ali and Warraich, 2023), mobile banking (Samsudeen et al. 2022), information communication technology in tourism (Ali et al. 2022), early warning systems in higher education (Raffaghelli et al. 2022), online learning (Batucan et al. 2022), mHealth (Alam et al. 2018), and wearable payment device (Al Mamun et al. 2023).

In the UTAUT model, the primary research focus is on extrinsic motivation, particularly PE, which reflects the perceived functionality and practical value of the technology and has the greatest impact on users' behavioral intention to adopt it (Venkatesh et al. 2003). Extrinsic motivation mainly refers to the extent to which the technology can meet users' work requirements and improve efficiency. Later, Venkatesh et al. (2012) proposed UTAUT2, which introduced intrinsic motivation and hedonic motivation (HM), expanding the original model. In addition to the four core constructs of UTAUT (EE, PE, SI, FC), UTAUT2 incorporated HM, which refers to the enjoyment and pleasure users experience when using the technology, thereby shifting the focus beyond practicality to consider user experience. In summary, the core relationships in the UTAUT model suggest that PE, EE, SI, and FC influence users' behavioral intention to use technology, while control variables moderate the impact of these core constructs. UTAUT2 further extended this by introducing HM, adding consideration of users' intrinsic motivation. Based on this, the research model in this study introduces usage years and age as moderating factors to develop this framework. Furthermore, this research incorporated actual usage behavior instead of relying solely on user intention from the perspective of new agricultural technologies.

Intention to use new agricultural technology (IU). Behavioral intention is defined as "the likelihood that a person may engage in certain behaviors and do something in the future under certain conditions" (Venkatesh et al. 2003). Intention to use new agricultural technology (IU) indicates the degree of intention to use and apply new agricultural technologies (Warshaw and Davis 1985). Studies have demonstrated that behavioral intention is a crucial factor in the acceptance of new technologies (Venkatesh et al. 2003; Kijsanayotin et al. 2009). In this context, IU denotes farmers' intention to adopt new technologies for use in agricultural production.

Performance expectancy (PE). PE, derived from the perceived usefulness of the technology acceptance mode, pertains to the degree to which an individual believes that technology can facilitate advancements in their work, such as enhancing efficiency (Ronaghi and Forouharfar, 2020). In research on new agricultural technologies, PE refers to the perceived effectiveness of new agricultural technologies in bringing about positive changes in various aspects of farming. This encompasses the anticipated benefits and improvements associated with the adoption and use of new agricultural technologies. PE is considered an influencing factor that directly determines a user's behavior or intention (Shiferaw and Mehari, 2019). Farmers are often driven by a desire to improve their yield and overall farm output. If they believe that adopting new agricultural technologies will improve efficiency, save time, increase productivity, or enhance the quality of their crops, they will be more inclined to embrace these technologies. Previous studies (Quaosar et al. 2018; Gansser and Reich, 2021) have consistently shown a significant connection between behavioral intention to adopt healthcare technology and PE. Moreover, a recent investigation by Shi et al. (2022) presented evidence supporting the notion that PE significantly impacts the inclination to invest in agricultural technologies. Consequently, we propose the following hypotheses:

H_1. *Performance expectancy has a positive influence on intention to use new agricultural technologies.*

Effort expectancy (EE). An individual's inclination to adopt a new technology is affected by its user-friendliness (Cimperman et al. 2016). In this context, EE pertains to how easily a farmer can employ new agricultural technologies (Sheng et al. 2016). Here, EE is influenced by perceptions related to the ease of cost management, learning, availability of time and energy, ease of transition, and suitability for operation. This reflects users' expectations regarding how effortless or challenging it is to integrate and use the new agricultural technology. The rational connection between EE and intention to use new agricultural technologies is rooted in the concept that farmers are more inclined to adopt technologies when they perceive them as easy to use, learn, and integrate. This inclination is heightened when the necessary resources are available and there is a sense of suitability for operation. Scholars (Quaosar et al. 2018; Zhang et al. 2017) have revealed that EE serves as a reliable indicator of intention in various technology adoption perspectives as well as willingness to pay for agricultural technology (Shi et al. 2022). Therefore, we hypothesize the following:

H_2. *Effort expectancy has a positive influence on intention to use new agricultural technology.*

Hedonic motivation (HM). HM is characterized by the extent to which the utilization of a new technology results in satisfaction or pleasure and plays a pivotal role in both the adoption and use of the technology (Venkatesh et al. 2012). It delineates the respondents' motivation to engage with the system or technology

(Schukat and Heise 2021). Specifically, HM pertains to the positive motivation of an individual and exhibits a unique form of multidimensionality applicable to both monetary and non-monetary aspects (Uematsu and Mishra 2011). HM encompasses intangible benefits, such as joy, fun, entertainment, and other aspects beyond utilitarian factors (usefulness, efficiency, performance, etc.) (Shi et al. 2022). HM, arising from preferences, enjoyment of learning, social interactions, and resource availability, contributes to a positive attitude and, consequently, a greater inclination to embrace and use new agricultural technology. Farmers are more inclined to use new agricultural technologies if they find them interesting and enjoyable (Alam et al. 2020; Hew et al. 2015). Thus, we hypothesize the following:

H_3. *Hedonic motivation has a positive effect on intention to use new agricultural technologies.*

Social influence (SI). SI is defined as "the importance and influence of people who are close to or important to the person who can persuade him or her to accept a new technology or measure" (Venkatesh et al. 2003). In this study, it denotes the extent to which social opinions and the perspectives and practices of influential individuals affect farmers' adoption of new agricultural technologies. According to Cao (2020), reference groups encompass individuals or collectives who play a pivotal role in comparing people based on their attitudes, intentions, and behaviors. The opinions and perspectives of peers and esteemed individuals can significantly sway an individual's preferences and decision-making processes (Wei et al. 2019), especially when these viewpoints align with perceived usefulness and ease of use (Rajak and Shaw 2021). Research suggests that social circles within the workplace have a substantial influence on shaping attitudes and perceptions by acting as facilitators or catalysts for technology adoption (Jedwab et al. 2022; Ljubicic et al. 2020; Rajak and Shaw 2021; Yadav et al. 2022). Building on prior studies, Sun and Jeyaraj (2013) concluded that SI is a crucial factor promoting the behavioral intention to adopt new technologies. Therefore, we hypothesize the following:

H_4. *Social influence has a positive effect on intention to use new agricultural technologies.*

Facilitating conditions (FC). FC include "users' attitudes towards organizational infrastructure and financial and technical support after acceptance of a new technology or measure" (Venkatesh et al. 2003). In this study, the FC component denotes the organizational or technical resources and facilities that are readily available to make the process of adopting a new agricultural technology easier for farmers. It delineates farmers' perceptions of the extent to which the organizational and technological infrastructure in agriculture supports the adoption of new agricultural technologies (Schukat and Heise 2021). Bhattacherjee and Hikmet (2008) and Boontarig et al. (2012) emphasize that FC are influential factors in shaping users' behavioral intentions toward adopting new technologies. Alam et al. (2020) discovered that FC have a positive impact on behavioral intention. The researchers emphasized the significance of FC, considering them to constitute a crucial factor determining a consumer's intention to adopt technology, as highlighted by Dwivedi et al. (2016). Hence, we propose the following hypothesis:

H_5. *Facilitating conditions have a positive effect on intention to use new agricultural technologies.*

Price value (PV). PV is an additional element incorporated into UTAUT 2 (Venkatesh et al. 2012). It is characterized by the consumer's perceived balance between the perceived system value and the cost associated with acquiring or using a new technology (Venkatesh et al. 2012). When utilizing new technologies, end users consistently evaluate the costs associated with the potential savings they may accrue from adopting those technologies (Baabdullah 2018; Alalwan 2020; Verdouw et al. 2016). With the use of new agricultural technologies, farmers' agricultural production will obtain productivity gains at a more favorable price than traditional agricultural production (Venkatesh et al. 2012). There is evidence supporting the significance of FC as a crucial factor in farmers' behavior when agricultural production adopts IoT (Shi et al. 2022). In this study, we hypothesize that the benefits of adopting new agricultural technologies for production outweigh their costs. Therefore, we hypothesize the following:

H_6. *Price value has a positive effect on intention to use new agricultural technologies.*

Usage of new agricultural technology (UN). The utilization patterns of new agricultural technologies refer to the actual degree of farmers' application of new agricultural technologies. Behavioral intention serves as a reliable factor for predicting behavior (Davis 1989; Fishbein and Ajzen 1977; Ajzen 1991) in many behavioral theoretical models. Venkatesh et al. (2003) conducted research on the adoption of information technology by users and indicated that use behavior is directly influenced by FC. In a separate investigation, Raza et al. (2021) discovered a positive correlation between FC and BI. Additionally, Boontarig et al. (2012) proposed in their research that FC has a positive effect on BI and behaviors related to smartphone use for health services. Likewise, if farmers have positive intentions, it is reflected in their motivation and readiness to adopt and use new agricultural technologies. The expectation of positive outcomes acts as the driving force. Many studies have proven that the greater the intention people have to use a technology, the more likely they are to actually use it (Ronaghi and Forouharfar, 2020; He et al. 2020; Ling Keong et al. 2012; Venkatesh et al. 2003). Therefore, we hypothesize the following:

$H_{7\text{-}8}$. *Facilitating condition and intention to use new agricultural technology has a positive effect on farmers' usage of new agricultural technologies.*

Moderation of age and using years. Different age groups have varying levels of experience, adaptability to technology, and perspectives on innovation. Younger farmers may be more tech-savvy and open to adopting new technologies, while older farmers may rely on traditional methods. Farmers with more years of experience using technology may have developed an improved understanding of the advantages and challenges associated with technological adoption. Their experiences may influence how they perceive and utilize new agricultural technologies.

Younger farmers or those with fewer using years may be more influenced by the perceived benefits of technology, whereas older farmers with more experience may rely on their past experience. Younger farmers may adapt more easily to new technologies, whereas older farmers may find it challenging to change their established practices. Similarly, younger farmers might be more motivated by the enjoyment and satisfaction derived from using technology, whereas older farmers may prioritize practical benefits. Younger farmers may be swayed more by peer trends and community dynamics, whereas older farmers may depend on their established networks. Likewise, younger farmers or those with fewer using years may be more sensitive to the cost-effectiveness of technology, whereas older farmers may prioritize reliability over cost. In addition, farmers with more using years may have encountered various FC and learned to navigate them, whereas younger farmers may rely more on external support.

According to Nikolopoulou et al. (2021), the effects of FC on technology usage may differ by age, with younger farmers being more receptive and responsive to new conditions, whereas older farmers may require more convincing or support. Additionally, the connection between FC and technology usage is influenced by the number of years a farmer has been using technology, and farmers with more experience may have developed a greater ability to leverage FC (Nikolopoulou et al. 2021). Therefore, age and using years can moderate the link between these factors and the UN, reflecting farmers' varying perspectives, experiences, and priorities at different stages of their careers and technology adoption.

$H_{9a\text{-}f}$. *Farmers' age moderates the relationship between performance expectancy, effort expectancy, hedonic motivation, social influence, price value, facilitating conditions, and intention to use new agricultural technology as well as between facilitating condition and use new agricultural technologies.*

$H_{10a\text{-}f}$. Using years *of technology moderates the relationship between performance expectancy, effort expectancy, hedonic motivation, social influence, price value, facilitating conditions, and intention to use new agricultural technology as well as between facilitating condition and use new agricultural technologies.*

Mediation of intention to use new agricultural technology. IU acts as a central cognitive factor that integrates the influences of PE, EE, HM, SI, and FC. Farmers who perceive technology as beneficial (PE), easy to use (EE), emotionally satisfying (HM), socially endorsed (SI), cost-effective (FC), and FC are more likely to form a positive intention to use the technology (Shi et al. 2022, Venkatesh et al. 2012). This positive intention, in turn, becomes a strong predictor of actual technology usage. Farmers with a favorable inclination are more inclined to translate that intention into action by adopting and using new agricultural technology on their farms (Ronaghi and Forouharfar, 2020; He et al. 2020). Therefore, we hypothesize the following:

$H_{M1\text{-}6}$. *Intention to use new agricultural technology mediates the relationship between performance expectancy, effort expectancy, hedonic motivation, social influence, price value, facilitating conditions, and use of new agricultural technologies.*

All association hypothesized above are presented in Fig. 1.

Research methodology

Sample selection and data collection. This quantitative cross-sectional study used an independent questionnaire as the main data-collection tool. The questionnaire responses provided a detailed and in-depth understanding of the acceptance of new agricultural technologies and the likelihood of rural smallholder farmers' future adoption behaviors in the Chinese region. According to the public information released by the National Bureau of Statistics' Bulletin on 2023 Summer Grain Production Data, Henan, Shandong, Anhui, Hebei, and Jiangsu are among the top five of China's 25 major production provinces in terms of production (National Bureau of Statistics Announcement on Summer Grain Production Data for 2023, 2023). Among them, Henan, Shandong, Hebei are in the northern regions of China, and Anhui and Jiangsu were selected as representatives of the southern regions. In this study, the provinces were screened and it was decided to select Henan and Jiangsu provinces as the sample representatives. Among them, Zhoukou's total grain production ranked first in Henan Province was selected, and Nantong was selected as the first production in Jiangsu Province. The main samples were groups of farmers in these cities who have become pioneers in China's agricultural modernization and adoption of new technologies owing to limited arable land resources and other factors. All of the participants provided written informed consent. To protect the security of respondents' personal information and avoid wasting resources on paper questionnaires, all questionnaires were distributed and collected through online questionnaire platforms and software. Considering reasons such as the dispersed residences of farmer groups and inconsistent farming hours, this research team obtained research permission by communicating with rural government units and departments and used the channels of rural governments and cooperatives to obtain contact information of farmers for online questionnaire distribution and collection. A convenience sampling technique was applied, meaning that we selected individuals who responded when researchers sent a link via social media and returned the completed form online.

The questionnaire selection procedure followed principles of voluntary participation and data confidentiality. Before deciding to participate, the respondents were thoroughly briefed on the content and objectives of the questionnaire and assured of their anonymity, confidentiality, and right to withdraw from the study. The sample size was determined using G*Power 3.1 (Faul et al. 2009). The appropriate sample size required when the effect size is 0.15, the power is 0.8, and there are nine predictors is 172. The second-generation statistical analysis technique of partial least squares structural equation modeling (PLS-SEM) was used in this study, and it usually requires a recommended sample size of at least 200 (Henseler et al. 2015). Therefore, 350 questionnaires were dispersed in this study, and 343 were returned. There were 326 (95.04%) valid responses. The researchers achieved a high response rate because they periodically reminded respondents to complete the questionnaires.

Survey instrument. This study designed a structured questionnaire to investigate and analyze farmers' acceptance of new agricultural technologies based on an intensive literature review. The survey instrument was segmented into two sections: Part A focused on the demographic characteristics of the respondents, such as age, education level, farm income, and the use of new agricultural technologies. Part B consisted of scale questions, and a seven-point Likert scale was used to assess the acceptance of farmers' adoption of new agricultural technologies. For example, the PE items were adapted from Molina-Maturano et al. (2021) and Giua et al. (2022); the HM items were adapted from Hu et al. (2022) and Schukat and Heise (2021); and the SI items were adapted from Molina-Maturano et al. (2022) and Schukat and Heise (2021). The items for SI were adapted from Xie et al. (2022) and Sun et al. (2021), whereas those for the FC were adapted from Shi et al. (2022) and Schukat and Heise (2021). The items for EE, FC, and IU were adapted from Xie et al. (2022). The UN construct items were based on Ronaghi and Forouharfar's (2020) study. The operational definition and complete questionnaire have been provided in Table 1 and Supplementary Material S1. *Survey Instrument* respectively.

Common method bias. Common method bias as assessed using Kock and Lynn (2012) full collinearity test to evaluate the presence of common method variance in the single-source data used in this study. All variance inflation factor (VIF) values were well below 3.3 (as shown in Table 2), signifying that there was no significant problem of common method bias in the data. Moreover, this research conducted an exploratory factor analysis of all of the variables by performing the Harman one-factor test, and according to the results of the analysis, the extracted variance of the first factor was 30.01%, which is less than the critical value of 40%, indicating the absence of common method bias in this study.

Fig. 1 Research framework.

Multivariate normality. The selection of appropriate data for analysis depends on the multivariate normality. We evaluated multivariate normality using the Web Power online tool (https://webpower.psychstat.org/wiki/tools/index). The multivariate *p* value determined for Mardia showed that there was an issue of non-normality in the study data, as the recorded *p* value was below 0.05 and the results indicated non-normality of the data (Cain et al. 2016).

Data analysis method. Considering that PLS-SEM is suitable for more complex structural and non-normal data, has been widely used in marketing and management research (Hair et al. 2019), and is a widely used predictive analytics methodology, it was adopted in this study. Henseler et al. (2009) argue that PLS-SEM can be effective in detecting and validating exploratory models in the early stages of theory development. Therefore, this study uses SmartPLS to test the causal relationships among the constructs. In addition, the measurement model was evaluated in this study using PLS-SEM considering several key aspects including, but not limited to, average variance extracted (AVE), internal consistency reliability, discriminant validity, effect size, predictive relevance, indicator reliability, path coefficient estimation, and convergent validity (Becker et al. 2022). Moreover, to better understand the relationships between the variables and explore the mechanisms and effects behind these relationships, this study introduces intention to adopt as a mediator and farmers' age and using years as intermediaries to understand and explore more comprehensively and in greater depth small-scale farmers' acceptance and use of new agricultural technologies in the Chinese region. In addition, this study used a combination of PLS-SEM and

Table 1 Operational definitions of variables.

Effort Expectancy	How easily a farmer can adopt new agricultural technologies, influenced by perceptions of cost management, learning ease, time and energy availability, transition smoothness, and operational suitability (Sheng et al. 2016).
Social Influence	The extent to which social opinions and the perspectives and practices of influential individuals affect farmers' adoption of new agricultural technologies.
Facilitating Conditions	The extent to which the organizational or technical resources and facilities in agriculture supports the adoption of new agricultural technologies (Schukat and Heise, 2021).
Performance Expectancy	The perceived effectiveness i.e., anticipated benefits and improvements associated with the adoption and use of new agricultural technologies.
Hedonic Motivation	The appeal of achieving economic benefits, the excitement of maximizing resource utilization for sustainable production, and the overall attractiveness and interest in engaging with innovative farming tools and methods.
Intention to Use New agricultural technology	Farmers' willingness to adopt, learn, and integrate new technologies, including trying, continuing use, and recommending them if effective.
Price Value	Farmers' assessment of the cost-effectiveness and financial benefits of new technologies, including reasonable pricing, reduced labor costs, improved efficiency, and higher profits.
Usage of New agricultural technology	The actual degree of farmers' application (how extensively and proficiently) of new agricultural technologies, including understanding their use, frequent application, skill mastery, and plans for increased future use.

Table 2 Full collinearity test.

Variables	PE	EE	HM	SI	FC	PV	IU	UN
VIF	2.192	1.506	1.468	1.369	1.477	1.355	1.437	1.480

Source: Author's data analysis.
EE Effort Expectancy, *SI* Social Influence, *FC* Facilitating Conditions, *PE* Performance Expectancy, *HM* Hedonic Motivation, *IU* Intention to Use New Agricultural Technology; *PV* Price Value; *UN* Usage of New Agricultural Technology.

multigroup analysis (MGA), considering that multi-group analysis is also effective in measuring the robustness and generalizability of the research framework and identifying potential sources of interference or confounding variables, which can improve the quality, credibility, and persuasiveness of the study (Cheah et al. 2023). This study ensured its robustness by subgrouping the group of farmers interviewed through different income levels and whether they had received financial subsidies from the government, training, or remote assistance.

Findings

Demographic characteristics. Table 3 presents the demographic details and various socio-economic characteristics of 326 respondents involved in agricultural activities. This table is comprehensive, covering aspects such as age distribution, years of using new agricultural technology, ownership and usage patterns of agricultural technology, educational background, government support, occupation, farm size, income levels, and the types of crops grown. The age distribution shows a significant portion of respondents (38%) are aged between 41 and 50 years, followed by those in the 51–60 years category (30.7%). This indicates a middle-aged demographic is heavily involved in agricultural activities. However, the adoption of new agricultural technologies is more pronounced among those who have been using it for 1–3 years (47.2%) and less than 1 year (32.5%). This suggests a growing interest or recent push towards technological adoption in agriculture among this age group. Educational attainment among respondents is predominantly at the secondary school level or below (45.4%), with only a small fraction (4.9%) having a bachelor's degree or higher. Despite the low levels of higher education, a substantial portion (60.1%) owns new agricultural technology, and an even higher percentage (88%) rents it, indicating that access to technology is not entirely dependent on educational background.

Government initiatives appear to be impactful, with 74.5% of respondents receiving government training and 71.2% receiving financial support. These figures suggest that government intervention plays a crucial role in promoting agricultural activities and technological adoption. Furthermore, a majority of the respondents (58.9%) are farmers with rural land contracts, signifying that land ownership remains a vital aspect of agricultural livelihoods. The majority of farms are small, with 38% being less than 10 mu (approximately 1.65 acres), while only a very small percentage (0.9%) are more than 1000 mu. This reflects the predominance of small-scale farming in the region. Income data aligns with this, as most farmers earn between 10,001 and 100,000 RMB annually (60.1%), while very few earn more than 1 million RMB (0.6%). Interestingly, a significant portion of respondents (71.2%) use agricultural-related social media platforms to seek remote assistance from experts, highlighting the importance of digital platforms in modern farming practices. The crop types grown are diverse, with wheat (87.4%) and rice (71.5%) being the most common, followed by fruits (48.8%) and vegetables (29.8%).

Validity and reliability. As recommended by Hair et al. (2019), this study analyzed the data through SEM via PLS-SEM and utilized measures to test and ensure the reliability and validity of the questionnaire. Specifically, Cronbach's alpha values for all measures were above 0.85, much higher than the suggested threshold of 0.7, indicating a high degree of consistency and reliability of the scale (Table 4). The findings indicated that the constructs' reliability was deemed high, as evidenced by the composite reliability values surpassing both the minimum cutoff of 0.70 and the endorsed threshold of 0.70, as suggested by Hair et al. (2017).

In addition, the validity of the questionnaire was evaluated by assessing convergent and discriminant validity, as suggested by

Table 3 Demographic details.

	N	%		N	%
Age			*Years of using New agricultural technology*		
18-30 Years	13	4	Less than 1 year	106	32.5
31-40 Years	41	12.6	1-3 years	154	47.2
41-50 Years	124	38	3-5 years	54	16.6
51-60 Years	100	30.7	more than 5 years	12	3.7
61-70 Years	34	10.4	Total	326	100
Above 70 Years	14	4.3			
Total	326	100	*Ownership of New agricultural technology (multiple choices)*		
			Owner	196	60.1
Educational background			Rent	287	88
Secondary school and below	148	45.4	Sharing	238	73
Senior middle school	143	43.9	Total	326	100
Higher education	19	5.8			
Bachelor or above degrees	16	4.9	*Have you received government training?*		
Total	326	100	Yes	243	74.5
			No	83	25.5
Have you received financial support from the government?			Total	326	100
Yes	232	71.2	*Occupation*		
No	94	28.8	Farmers working outside	134	41.1
Total	326	100	Farmers with rural land contract	192	58.9
			Total	326	100
Farm Size (mu)					
Less than 10	124	38	*Have you used agricultural related social media platforms to seek remote assistance from experts?*		
10-100	101	31			
100-400	59	18.1	Yes	232	71.2
400-700	31	9.5	No	94	28.8
700-1000	8	2.5	Total	326	100
more than 1000	3	0.9			
Total	326	100	*Types of crops grown (multiple choices)*		
			Rice	233	71.5
Annual Income from Firming			Wheat	285	87.4
Less than 10,000RMB	41	12.6	Soybeans	134	41.1
10,001-100,000RMB	196	60.1	Corn	143	43.9
100,001-1 Million RMB	87	26.7	Vegetables	97	29.8
More than 1 Million RMB	2	0.6	Fruits	159	48.8
Total	326	1000	Others	10	3.1
			Total	326	100

1 Mu = 0.165 Acre; 1RMB = 0.14USD.

Hair et al. (2019), with the former measured by the AVE and factor loadings. The AVE values recorded in Table 4 are all well above the suggested threshold of 0.50, indicating that convergent validity is acceptable. Discriminant validity was assessed based on the Fornell-Larcker criterion proposed by Avkiran and Ringle (2018) and the Heterotrait-Monotrait Ratio (HTMT); detailed data are shown in Table 5. The HTMT values of all of the items are below 0.60, which is far below the threshold value of 0.85, indicating that the HTMT values between dimensions are within the range of significance, and the questionnaire's discriminant validity is satisfactory.

The loading and cross-loading values (see Appendix A) indicate that all of the loading values are greater than 0.5, which is higher than the respective cross-loadings. The evaluation of the VIF additionally confirmed the absence of interconnections among the independent variables as the recorded values ranged from 1.421 to 2.166, falling within the acceptable range of less than 5, as indicated by Hair et al. (2019). Consequently, multicollinearity was excluded, and the correlation structure within the measurement model was deemed suitable.

Structural Model. Figure 2 and Table 6 present the results of testing the hypotheses. The constructs PE (H_1: $\beta = 0.135$, $p < 0.05$), EE (H_2: $\beta = 0.216$, $p < 0.05$), and HM (H_3: $\beta = 0.178$, $p < 0.05$) had a significant positive effect on IU, while the constructs SI (H_4: $\beta = 0.060$, $p > 0.05$), FC (H_5: $\beta = 0.083$, $p > 0.05$), and PV (H_6: $\beta = 0.077$, $p > 0.05$) become insignificant with IU at the 5% level of significance. Likewise, IU (H_8: $\beta = 0.216$, $p < 0.05$) and FC (H_7: $\beta = 0.299$, $p < 0.05$) had a significant positive effect on UN at the 5% level of significance. Therefore, H_4, H_5, and H_6 were rejected, and only H_1, H_2, H_3, H_7, and H_8 were supported (Table 6).

According to the moderating effect of age and using years (Table 6), the empirical results indicate that age does not moderate any of the relationship [PE (H_{9a}: $\beta = 0.106$, $p > 0.05$), EE (H_{9b}: $\beta = 0.026$, $p > 0.05$), HM (H_{9c}: $\beta = -0.067$, $p > 0.05$), SI (H_{9d}: $\beta = -0.087$, $p > 0.05$), FC (H_{9e}: $\beta = 0.009$, $p > 0.05$), PV (H_{9f}: $\beta = 0.027$, $p > 0.05$) and IU] proposed at the 5% level of significance. In addition, using years only moderates the relationship between PE (H_{10a}: $\beta = 0.142$, $p < 0.05$) and IU as well as that between PV (H_{10f}: $\beta = -0.120$, $p < 0.05$) and IU. The other moderating relationships of using years with EE (H_{10b}: $\beta = -0.029$, $p > 0.05$), HM (H_{10c}: $\beta = -0.050$, $p > 0.05$), SI (H_{10d}: $\beta = 0.033$, $p > 0.05$), FC (H_{10e}: $\beta = 0.041$, $p > 0.05$), and IU become insignificant at the 5% level of significance. Thus, H_{10a} and H_{10f} were supported, whereas $H_{9a\text{-}f}$, $H_{10b\text{-}e}$ were rejected.

For mediating effects, the outcomes in Table 6 show that IU had a significant and positive mediating influence on the relationship between EE (H_{M2}: $\beta = 0.047$, $p < 0.0.5$), HM (H_{M3}: $\beta = 0.038$, $p < 0.05$), and UN. For these mediating effects, the 90% confidence intervals were statistically significant, as they did not encompass zero within the 5–95% confidence intervals. In contrast, IU's mediation in the relationships between PE (H_{M1}: $\beta = 0.029$, $p > 0.0.5$), SI (H_{M4}: $\beta = 0.013$, $p > 0.0.5$), FC (H_{M5}: $\beta = 0.018$, $p > 0.0.5$), and PV (H_{M6}: $\beta = 0.017$, $p > 0.0.5$) and UN become insignificant at the 5% level of significance.

Bootstrap analyses were conducted using SmartPLS 4. The coefficients of determination (R^2) and effect sizes (f^2) were obtained from a large bootstrap subsample (5000), and the predictive relevance of the PLS pathway model was assessed by calculating predictive relevance (Q^2) values. In this model, the R^2 for IU was 0.346, indicating that exogenous constructs explained 34.6% of the variance in ecological worldviews. The coefficient of determination for UN was 0.196, with exogenous constructs explaining 19.6% of the variance in UN. Hair et al. (2017) suggested that the importance of independent constructs in explaining dependent constructs can be measured by assessing the effect size (f^2). The f^2 thresholds of 0.005, 0.01, and 0.025 explain small, medium, and large effects of the measured variables, respectively (Avkiran and Ringle 2018). The data in Table 4 show that the effect sizes of EE and HM on IU exceeded 0.025, and the effect sizes of FC and IU on UN were much larger than 0.025; that is, the effect sizes were large. The effect size of PE on IU ($f^2 = 0.013$) was higher than 0.01 but lower than 0.025, indicating a medium effect size. In this study, the effect size of SI on IU was 0.004, that of FC on IU was 0.007, and that of PV on

Table 4 Reliability and validity.

Variables	Items	Mean	Std. Deviation	Cronbach's alpha	DH_rho	Composite reliability	Average variance extracted	VIF
PE	5	4.847	1.337	0.882	0.884	0.914	0.679	2.166
EE	5	5.142	1.204	0.892	0.900	0.920	0.698	1.480
HM	5	5.288	1.174	0.883	0.887	0.914	0.680	1.466
SI	5	4.982	1.289	0.878	0.885	0.910	0.670	1.435
FC	5	5.101	1.152	0.865	0.876	0.902	0.648	1.520
PV	5	4.961	1.159	0.851	0.865	0.892	0.623	1.421
IU	5	5.398	1.183	0.876	0.877	0.910	0.669	1.165
UN	5	4.856	1.314	0.879	0.885	0.911	0.673	-

Source: Author's data analysis.
EE Effort Expectancy, *SI* Social Influence, *FC* Facilitating Conditions, *PE* Performance Expectancy, *HM* Hedonic Motivation, *IU* Intention to Use New Agricultural Technology, *PV* Price Value, *UN* Usage of New Agricultural Technology.

Table 5 Discriminant validity.

	PE	EE	HM	SI	FC	PV	IU	UN
Fornell-Larcker Criterion								
PE	0.824							
EE	0.489	0.836						
HM	0.496	0.259	0.824					
SI	0.464	0.241	0.289	0.819				
FC	0.505	0.304	0.366	0.399	0.805			
PV	0.443	0.390	0.268	0.296	0.284	0.790		
IU	0.456	0.416	0.384	0.293	0.326	0.294	0.818	
UN	0.497	0.375	0.397	0.341	0.382	0.275	0.311	0.820
Heterotrait-monotrait ratio (HTMT)								
PE								
EE	0.549							
HM	0.562	0.288						
SI	0.522	0.269	0.326					
FC	0.572	0.347	0.418	0.454				
PV	0.514	0.454	0.307	0.349	0.327			
IU	0.516	0.463	0.433	0.327	0.373	0.329		
UN	0.563	0.419	0.452	0.385	0.427	0.322	0.349	

Source: Author's data analysis.
EE Effort Expectancy, *SI* Social Influence, *FC* Facilitating Conditions, *PE* Performance Expectancy, *HM* Hedonic Motivation, *IU* Intention to Use New Agricultural Technology, *PV* Price Value, *UN* Usage of New Agricultural Technology.

IU was 0.006. These effect sizes were all approximately 0.005, indicating small or very small effects. Finally, according to Table 7, the predictive relevance (Q^2) value for the blindfold method is above zero, indicating that the model is predictively relevant.

Multigroup analysis. To enhance our understanding of the results, we implemented a MGA approach. Complying with the advice outlined by Hair et al. (2019), we applied the MGA method to explore moderation effects across various relationships and scrutinize potential heterogeneity within subgroups. Prior to the execution of the MGA, we used the measurement invariance of composite models (MICOM) approach to assess the level of consistency between the two groups. This preliminary step aimed to gauge the uniformity of measurement across groups to ensure reliability and comparability of the data. Through this systematic two-step process, we sought to establish a robust foundation for valid comparisons of the structural model parameters, enabling a more thorough and nuanced approach. Interpretation of potential variations in key variables across diverse subgroups within the study population.

The outcomes (see Table 8) show that no significant difference was found across income levels (income [greater/less than 100 K RMB], financial support [receiving or not receiving government financial support], remote assistance [having or not having remote assistance], technology ownership [Yes/No] training [having/not having received technical training from governmental organizations]). This is similar for the technology ownership categories (owning/not owning technology) and the above-mentioned relationships, except for the user-year interaction of the FC, SI, and IU relationships. All constructs exhibited permutation p-values above 0.05, confirming measurement invariance within the groups under examination. Subsequently, PLS-MGA was employed to scrutinize the path coefficient values.

Discussions

In this investigation, we examined the predictors affecting the adoption of new agricultural technologies in small rural farming communities and discussed the implications of our discoveries. Grounded in the UTAUT framework, we formulated 24 hypotheses, of which nine were substantiated through empirical analysis. These results highlight the substantial impact of independent constructs on dependent constructs. Notably, the IU exhibited significant explanatory power, accounting for 34.6%, indicating a well-fitted model for our study. In the following section, we examine the relationships identified in our research and provide insights into key observations.

The statistically significant connection between PE and IU as supported by the data underscores the essential role of perceived utility in shaping users' willingness to adopt a new agricultural technology. This finding supports the results of previous studies (Quaosar et al. 2018; Shi et al. 2022). PE captures users' perceptions of how adopting a new technology contributes to achieving their performance goals. In an agricultural context, this could include improvements in productivity, yield, resource management, and overall operational efficiency. The positive coefficient suggests that, as users perceive a higher utility in the technology, their intention to incorporate it into their agricultural practices increases. As expected, Hypothesis 2 asserts a positive connection between EE and IU. The data support this hypothesis, revealing a statistically significant and positive coefficient and indicating that as users perceive technology to be easier to use, their intention to adopt it increases, which is consistent with previous studies (Shi et al. 2022; Quaosar et al. 2018; Zhang et al. 2017). EE reflects user perceptions of the ease of using technology. Ease of use is critical in the context of agriculture, where users may have diverse levels of technological literacy. A positive connection indicates that users are more likely to embrace new agricultural technology when they perceive it as intuitive, user-friendly, and requiring minimal effort to operate. Agricultural technologies often require the incorporation of advanced features to address complex farming challenges. Striking a balance between providing advanced functionalities and ensuring a user-

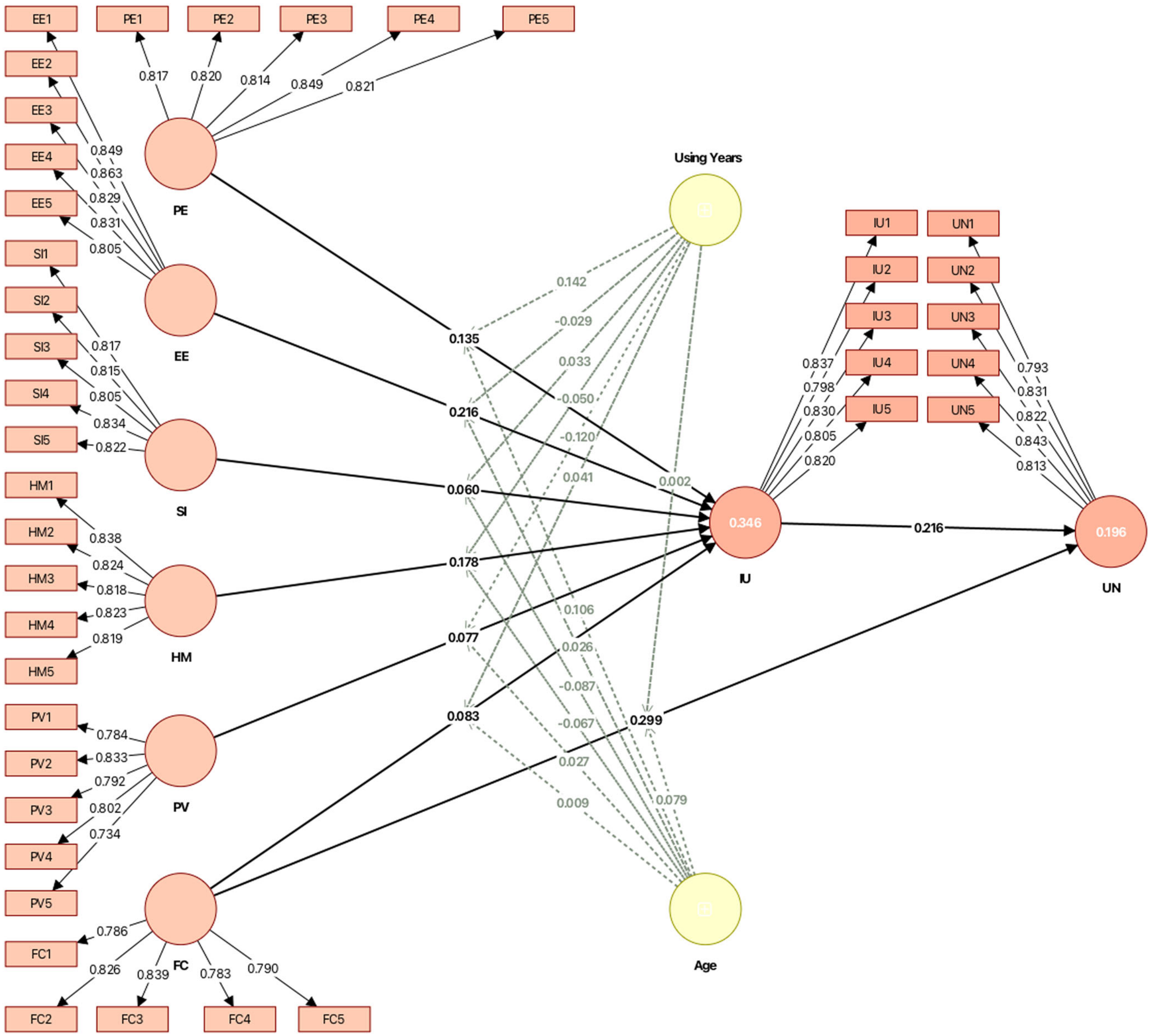

Fig. 2 Structural model.

friendly interface is crucial to meeting the diverse needs of users. Similarly, Hypothesis 3 posits a positive connection between HM and IU. The data supported this hypothesis, revealing a statistically significant and positive coefficient. Scholars (Shi et al. 2022; Alam et al. 2020; Hew et al. 2015) support these results as well, suggesting that users' HMs, such as enjoyment or pleasure, positively influence their intention to adopt a technology. HM introduces aspects of pleasure or enjoyment associated with using technology. In the context of agriculture, where traditional practices may not always be considered enjoyable, the introduction of technology that provides a positive and satisfying experience can significantly impact users' intention to adopt. This emotional connection can be a powerful driver of technology adoption.

Surprisingly, the data do not support sH_4, H_5, or H_6, indicating that SI (social factors), users' perceptions of organizational and technical support (FC), and perceived value for the price (PV) may not significantly influence IU. This contrasts with the findings of Shi et al. (2022) and Venkatesh et al. (2012). This finding (H_4) challenges the conventional wisdom that social factors play a significant role in technology adoption. In the agricultural context, where practices are often deeply rooted in tradition and individual experiences, the impact of SI may be less pronounced. This highlights the need for a more nuanced understanding of the specific social dynamics that contribute to the adoption of technology in agriculture. This finding (H_5) raises questions about the role of organizational and technical support in shaping user intentions. It is crucial to investigate whether users prioritize other factors such as usability or perceived benefits in the presence of FC. Additionally, organizational strategies to enhance support mechanisms may need to be tailored to user-specific needs and challenges. Likewise, this result (H_6) prompts a critical examination of how users perceive the value proposition concerning the cost of adopting new agricultural technology. It may be that other factors, such as PE or ease of use, weigh more heavily on users' decision-making processes. Understanding the specific features or benefits that users prioritize when considering the cost-value relationship is crucial for refining pricing strategies. However, the lack of support for H_4, H_5 and H_6 underscores the contextual variability in technology adoption within the

Table 6 Hypothesis testing.

Hypothesis		Beta	CI	t-value	*p* value	R^2	f^2	Supported?
H_1	PE → IU	0.135	(0.026, 0.255)	1.933	0.027	0.346	0.013	Yes
H_2	EE → IU	0.216	(0.111, 0.343)	3.049	0.001		0.048	Yes
H_3	HM → IU	0.178	(0.053, 0.289)	2.483	0.007		0.033	Yes
H_4	SI →IU	0.060	(-0.045, 0.166)	0.929	0.177		0.004	No
H_5	FC → IU	0.083	(-0.035, 0.185)	1.244	0.107		0.007	No
H_6	PV → IU	0.077	(-0.013, 0.163)	1.452	0.073		0.006	No
H_7	FC → UN	0.299	(0.194, 0.409)	4.617	0.000	0.196	0.097	Yes
H_8	IU → UN	0.216	(0.120, 0.317)	3.563	0.000		0.050	Yes
Moderating relationships								
H_{9a}	Age*PE → IU	0.106	(-0.03, 0.247)	1.243	0.107		0.006	No
H_{9b}	Age*EE → IU	0.026	(-0.094, 0.147)	0.355	0.361		0.001	No
H_{9c}	Age*HM → IU	-0.067	(-0.175, 0.054)	0.961	0.168		0.005	No
H_{9d}	Age*SI →IU	-0.087	(-0.207, 0.058)	1.064	0.144		0.006	No
H_{9e}	Age*FC → IU	0.009	(-0.131, 0.121)	0.124	0.451		0.000	No
H_{9f}	Age*PV → IU	0.027	(-0.082, 0.125)	0.442	0.329		0.001	No
H_{10a}	Using Years*PE → IU	0.142	(0.010, 0.285)	1.699	0.045		0.014	Yes
H_{10b}	Using Years*EE → IU	-0.029	(-0.134, 0.112)	0.385	0.350		0.001	No
H_{10c}	Using Years*HM →IU	-0.050	(-0.177, 0.054)	0.703	0.241		0.003	No
H_{10d}	Using Years*SI → IU	0.033	(-0.093, 0.150)	0.441	0.329		0.001	No
H_{10e}	Using Years*FC → IU	0.041	(-0.085, 0.167)	0.539	0.295		0.002	No
H_{10f}	Using Years*PV → IU	-0.120	(-0.233, -0.008)	1.757	0.039		0.016	Yes
Mediating relationships								
H_{M1}	PE → IU→ UN	0.029	(0.004, 0.067)	1.495	0.067			No
H_{M2}	EE → IU→ UN	0.047	(0.019, 0.085)	2.294	0.011			Yes
H_{M3}	HM → IU→ UN	0.038	(0.009, 0.073)	1.929	0.027			Yes
H_{M4}	SI → IU→ UN	0.013	(-0.009, 0.041)	0.836	0.202			No
H_{M5}	FC → IU→ UN	0.018	(-0.007, 0.044)	1.150	0.125			No
H_{M6}	PV → IU→ UN	0.017	(-0.003, 0.038)	1.331	0.092			No

Source: Author's data analysis
EE Effort Expectancy, *SI* Social Influence, *FC* Facilitating Conditions, *PE* Performance Expectancy, *HM* Hedonic Motivation, *IU* Intention to Use New Agricultural Technology, *PV* Price Value, *UN* Usage of New Agricultural Technology.

Table 7 PLS predict.

Items	Q^2predict	PLS-SEM_RMSE	LM_RMSE	Difference (RMSE)	PLS-SEM_MAE	LM_MAE	Difference (MAE)
IU1	0.132	1.354	1.396	−0.042	1.025	1.083	−0.058
IU2	0.110	1.345	1.371	−0.026	1.020	1.062	−0.042
IU3	0.128	1.344	1.378	−0.034	1.012	1.059	−0.047
IU4	0.142	1.345	1.426	−0.081	1.012	1.077	−0.065
IU5	0.120	1.384	1.453	−0.069	1.070	1.118	−0.048
UN1	0.113	1.535	1.523	0.012	1.194	1.191	0.003
UN2	0.120	1.548	1.571	−0.023	1.205	1.225	−0.020
UN3	0.118	1.495	1.522	−0.027	1.173	1.184	−0.011
UN4	0.143	1.458	1.476	−0.018	1.143	1.134	0.009
UN5	0.134	1.464	1.538	−0.074	1.136	1.182	−0.046

Source: Author's data analysis
EE Effort Expectancy, *SI* Social Influence, *FC* Facilitating Conditions, *PE* Performance Expectancy, *HM* Hedonic Motivation, *IU* Intention to Use New Agricultural Technology, *PV* Price Value, *UN* Usage of New Agricultural Technology.

agricultural sector. User characteristics, organizational context, and economic considerations may interact in complex ways, thereby influencing the significance of these factors.

H_7 and H_8 propose a positive connection between FC and IU. The data support these hypotheses, signifying that perceived organizational and technical support and favorable intentions significantly influence UN. This finding aligns with Raza et al. (2021) and Boontarig et al. (2012) and the expectation that supportive conditions play a crucial role not only in shaping users' intentions but also in translating those intentions into actual usage. Organizations and stakeholders should recognize the importance of creating an environment that facilitates the effective and seamless use of new agricultural technology, including providing the necessary resources, training, and technical support. The positive relationship between IU and UN is in line with the findings of Raza et al. (2021), Ronaghi and Forouharfar (2020), and He et al. (2020) and the widely accepted notion that intention is a significant precursor to actual behavior. However, it is important to recognize that, while intention is a strong predictor, various external factors, including FC, may mediate or moderate the relationship between intention and actual usage. Therefore, interventions aimed at increasing technology usage should not only focus on shaping users' intentions but also on creating an enabling environment.

The mediation effect test revealed that both EE and HM play significant roles in influencing the UN through the IU. This finding suggests that farmers do not adopt new technology simply because it is easy to learn or use. Instead, adoption is driven by a

Table 8 Multigroup analysis.

Associations	Income			Financial Support		
	Income <= 100 K RMB vs Income >100 K			No vs Yes		
	Difference	2-tailed *p* value	Decision	Difference	2-tailed *p* value	Decision
PE → IU	-0.031	0.427	No difference	0.189	0.190	No difference
EE → IU	-0.177	0.150	No difference	0.274	0.052	No difference
HM → IU	0.415	0.081	No difference	-0.248	0.081	No difference
SI → IU	0.227	0.084	No difference	-0.219	0.135	No difference
FC → IU	0.123	0.236	No difference	0.018	0.454	No difference
PV → IU	0.514	0.100	No difference	0.043	0.376	No difference
FC→UN	0.010	0.439	No difference	0.145	0.177	No difference
IU → UN	0.275	0.105	No difference	-0.073	0.306	No difference
Age*PE → IU	0.186	0.213	No difference	0.287	0.106	No difference
Age*EE → IU	-0.017	0.465	No difference	-0.095	0.291	No difference
Age*HM → IU	-0.138	0.208	No difference	-0.264	0.096	No difference
Age*SI →IU	0.076	0.347	No difference	-0.031	0.439	No difference
Age*FC → IU	0.303	0.062	No difference	0.034	0.428	No difference
Age*PV → IU	0.130	0.225	No difference	-0.001	0.499	No difference
Using Years*PE → IU	0.256	0.170	No difference	0.278	0.134	No difference
Using Years*EE → IU	-0.051	0.383	No difference	-0.012	0.469	No difference
Using Years*HM → IU	-0.233	0.084	No difference	-0.147	0.257	No difference
Using Years*SI → IU	0.272	0.064	No difference	0.068	0.367	No difference
Using Years*FC → IU	-0.146	0.192	No difference	0.072	0.361	No difference
Using Years*PV → IU	-0.088	0.311	No difference	-0.184	0.235	No difference
	Remote Assistance			Tech Ownership		
	No vs Yes			No vs Yes		
	Difference	2-tailed p value	Decision	Difference	2-tailed p value	Decision
PE → IU	0.043	0.435	No difference	0.170	0.136	No difference
EE → IU	0.138	0.225	No difference	0.194	0.103	No difference
HM → IU	-0.051	0.416	No difference	-0.095	0.271	No difference
SI → IU	-0.050	0.373	No difference	-0.144	0.171	No difference
FC → IU	0.065	0.344	No difference	-0.034	0.418	No difference
PV → IU	-0.023	0.437	No difference	-0.181	0.071	No difference
FC→UN	0.053	0.344	No difference	-0.181	0.094	No difference
IU → UN	0.072	0.302	No difference	0.130	0.135	No difference
Age*PE → IU	0.132	0.286	No difference	0.100	0.325	No difference
Age*EE → IU	0.136	0.238	No difference	0.050	0.377	No difference
Age*HM → IU	-0.213	0.143	No difference	0.103	0.270	No difference
Age*SI →IU	0.104	0.316	No difference	0.071	0.377	No difference
Age*FC → IU	-0.077	0.333	No difference	-0.309	0.037	Difference
Age*PV → IU	0.042	0.393	No difference	0.161	0.137	No difference
Using Years*PE → IU	0.252	0.146	No difference	0.140	0.241	No difference
Using Years*EE → IU	-0.208	0.181	No difference	0.009	0.474	No difference
Using Years*HM → IU	-0.057	0.412	No difference	0.102	0.253	No difference
Using Years*SI → IU	-0.159	0.231	No difference	-0.354	0.028	Difference
Using Years*FC → IU	0.080	0.355	No difference	-0.247	0.065	No difference
Using Years*PV → IU	0.035	0.434	No difference	0.196	0.102	No difference
	Training					
	No vs Yes					
	Difference	2-tailed *p* value	Decision			
PE → IU	0.262	0.135	No difference			
EE → IU	0.112	0.247	No difference			
HM → IU	-0.312	0.071	No difference			
SI → IU	-0.120	0.301	No difference			
FC → IU	0.068	0.341	No difference			
PV → IU	0.083	0.288	No difference			
FC→UN	0.159	0.137	No difference			
IU → UN	-0.002	0.498	No difference			
Age*PE → IU	0.149	0.257	No difference			
Age*EE → IU	0.074	0.355	No difference			
Age*HM → IU	-0.201	0.165	No difference			
Age*SI →IU	0.070	0.384	No difference			
Age*FC → IU	-0.054	0.394	No difference			
Age*PV → IU	-0.015	0.466	No difference			
Using Years*PE → IU	0.367	0.085	No difference			
Using Years*EE → IU	-0.120	0.292	No difference			

Table 8 (continued)

Associations	Income			Financial Support		
	Income <= 100 K RMB vs Income >100 K			No vs Yes		
	Difference	2-tailed *p* value	Decision	Difference	2-tailed *p* value	Decision
Using Years*HM → IU	-0.331	0.091	No difference			
Using Years*SI → IU	0.005	0.490	No difference			
Using Years*FC → IU	0.151	0.226	No difference			
Using Years*PV → IU	-0.083	0.386	No difference			

Source: Author's data analysis.
EE Effort Expectancy, *SI* Social Influence, *FC* Facilitating Conditions, *PE* Performance Expectancy, *HM* Hedonic Motivation, *IU* Intention to Use New Agricultural Technology, *PV* Price Value, *UN* Usage of New Agricultural Technology.

more complex, rational decision-making process where farmers evaluate the anticipated effort alongside their willingness to adopt the technology. Moreover, the enjoyment and intrinsic satisfaction derived from using the technology—key components of hedonic motivation—further motivate farmers to adopt and continue using it. In contrast, factors such as PE, SI, FC, and PV were not significant mediators in this process. These insights highlight the need for strategies that not only make new technologies easier to use but also enhance the psychological appeal and perceived long-term benefits, thereby encouraging broader adoption among farmers.

Unexpectedly, age did not have a moderating effect, while the moderating effect of the number of years using new agricultural technologies was very limited. Specifically, it positively moderated performance expectations, negatively moderated FC, and had no moderating effect on other variables. These findings align with those reported by Nikolopoulou et al. (2021), suggesting that while experience with technology can enhance certain expectations, it may simultaneously reduce the perceived ease of access to supportive resources. This could imply that as farmers become more experienced, they might develop higher expectations of performance but also face diminishing returns in the availability or perceived usefulness of organizational and technical support. The absence of a moderating effect of age might indicate that age-related differences in technology adoption are less significant than previously assumed, perhaps due to the increasing familiarity of older generations with technology. These nuanced interactions highlight the complexity of factors influencing technology adoption and underscore the need for further research to explore the conditions under which these moderating effects manifest.

The multi-group analysis demonstrated that the hypothesized model held consistent across various subgroups, such as income levels, financial support, remote assistance, technology ownership, and training exposure. Despite slight variations in the parameter estimates, none of these differences were statistically significant across the groups examined. This consistency implies that the predictors influencing IU and UN are stable and apply broadly across different demographic and contextual categories within the study population. The lack of significant differences across income, remote assistance, technology ownership, and training exposure suggests that these factors do not substantially alter the pathways by which the intention to adopt new technologies translates into actual usage. This indicates that the determinants of technology adoption are likely universal in this context, making it possible to apply general strategies across diverse groups without extensive customization. However, it is crucial to note that while the model's stability across these groups is advantageous for developing broad-based interventions, it also points to the need for further exploration. The results could imply that other unmeasured factors, such as cultural, behavioral, or psychological aspects, may play a more critical role in influencing technology adoption than the variables examined here. Additionally, even though the model appears robust across different subgroups, understanding the specific context and population remains essential when applying these findings to other settings. This approach ensures that while broad strategies are effective, they also remain sensitive to subtle differences in how various groups might perceive and interact with new agricultural technologies. Bring this discussion into a paragraph.

Implications

Theoretical implications. This research offers the advancement of theoretical frameworks in several key areas. *First*, the study's focus on agricultural technology adoption brings a context-specific lens to the theoretical discourse. These findings highlight the ecological validity of the theoretical framework in the agricultural domain and emphasize the need for context-specific considerations to understand and predict technology adoption in this sector. This contextualization contributes to the broader literature on the applicability and generalizability of technology adoption theories in different domains.

Second, this study refines technology adoption theories, such as UTAUT, providing new perspectives and methods for research in related fields. While the UTAUT model initially focused on external motivational factors (such as PE, EE, SI, and FC), this research broadens the model's applicability and explanatory power by integrating intrinsic motivation (HM) and PV from UTAUT2, and by incorporating moderating variables like years of use and age. This expansion further enriches the theoretical framework.

Third, the study revealed that not all determinants exert equal influence on the intention to use and actual UN. While constructs such as PE, EE, and HM significantly affect intention, factors such as SI, FC, and PV have no significant influence. This selective impact underscores the need for a nuanced perspective of the determinants of technology adoption, moving beyond a one-size-fits-all approach. In addition, the coefficients of determination (R^2) and effect sizes (f^2) provided insights into the robustness of the predictive model. The substantial effect sizes observed for certain constructs such as EE, HM, FC, and IU on UN contribute to the ongoing discourse on the importance of specific factors in explaining the variance in technology adoption outcomes. This emphasis on robust predictive models contributes to the methodological rigor in technology adoption research.

Fourth, identifying age and using years as potential moderators sheds light on the intricate relationship between individual characteristics and technology adoption. Age was not found to moderate any relationship, suggesting a consistent impact across age groups. However, using years emerged as a moderator, influencing the link between PE and IU as well as that between PV and IU. This finding introduces a temporal dimension to UTAUT2, indicating that users' accumulated experience with technology over time significantly influences their adoption decisions. By understanding how users' perceptions evolve with prolonged technology use, this study offers a dynamic perspective on UTAUT.

Fifth, the interconnectedness of constructs, such as the mediating role of intention and the shared influence of FC on both intention and actual usage, emphasizes the complex interplay among the determinants. The interrelationships among these constructs suggest that multiple factors interact during the technology adoption process, collectively shaping users' decisions and behaviors. Notably, the significant impact of FC on actual adoption behavior underscores the importance of external support in promoting the successful adoption and utilization of technology, even if FC does not significantly influence adoption intention. FC have a significant positive impact on actual usage behavior, indicating that supportive conditions are crucial for users to integrate technology into agricultural practices. This finding provides valuable insights for technology promotion policies and implementation strategies, emphasizing the necessity of creating an environment that effectively supports users in continuously using new technologies to ensure their long-term success.

Practical implications. The study offers several policy implications; *first*, the effort expectation (ease of use) of new agricultural technologies can quickly mobilize the enthusiasm of farmers to accept new technologies, generate willingness to adopt, and then, through willingness to adopt, influence the adoption behavior of farmers. For simple technologies, such spontaneous dissemination is effective. However, for more complex agricultural innovations, government organizations at various levels (such as county and village levels) need to adopt proactive promotion measures to enhance farmers' adoption intentions. It is necessary for grassroots government organizations to build a more systematic training system for the new agricultural technology and for society, such as agricultural extension workers, agricultural experts, agricultural research institutes, and government organizations, to build a more systematic training system for new agricultural technology. This requires the active participation of all sectors of society, including agricultural extension workers, experts, research institutes, and enterprises. Combined with the research data in this study and the current situation of improving the literacy level of the whole society, it is recommended that we focus on training younger farmers with higher literacy levels or learning intention to drive the potential acceptance of farmers around them to realize the rapid dissemination of new agricultural technologies and to form a strong learning atmosphere in the promotion of new agricultural technologies, accelerate the modernization of agriculture, and improve the efficiency of agricultural production.

Second, FC (such as policy concessions, free training, and the provision of related equipment and resources) have a significant impact on the actual use of technology. Governments at all levels should formulate policies that facilitate the adoption of new agricultural technologies and actively promote the implementation of such policies by linking upward and downward to provide policy support and financial subsidies for new agricultural technologies with better results, building an information platform for the exchange of agricultural technologies, introducing relevant videos on the provision of new technologies, and attracting agricultural experts and agribusinesses to settle in the area to facilitate the use of technologies by farmers and reduce the cost of use. Promote the agricultural production behavior of farmers using new agricultural technologies. Traditional village committees, agricultural machinery stations, and other grassroots units should make full use of their advantage of having close contact with farmers and incorporate them into the informatization exchange platform, which will help them discover and resolve the difficulties and experiences in the process of promoting new agricultural technologies in a timely manner and will help popularize new agricultural technologies among farmers.

Third, although the impacts of SI, FC, and PV on adoption intention are not significant, education and awareness enhancement remain crucial. Educational and awareness programs should focus on improving users' understanding of the practical benefits and value propositions of new technologies, highlighting their actual advantages, and addressing potential issues to foster positive attitudes and intentions. In addition, this study emphasized the significant positive influence of technology-related training on both intention and actual usage. Policymakers and agricultural organizations should invest in comprehensive training programs to equip users with the necessary skills and knowledge. Policymakers, researchers, and technology developers should be encouraged to share knowledge and best practices to foster continuous learning and collaboration, thereby accelerating the process of technology adoption. Additionally, policymakers may consider introducing incentives or subsidies to adopt new agricultural technologies, particularly for users facing financial constraints (Reddy et al. 2023). In light of the finding that PV does not significantly impact intention, financial incentives may serve as a catalyst by encouraging users to overcome financial barriers and thus expedite the adoption process.

Fourth, to ensure the successful adoption and sustained use of new technologies, stakeholders should adopt a long-term engagement strategy. Continuous communication, user support, and feedback mechanisms are crucial for maintaining positive adoption intentions. It is essential to establish and maintain these feedback mechanisms to ensure the long-term effective application of new agricultural technologies.

Conclusion, limitations, and future recommendations

In conclusion, we explored the factors shaping the uptake of new agricultural technology in small rural farming communities and examined the consequences of our findings. Notably, the PE, EE, and HM constructs demonstrated a statistically significant positive impact on IU. Conversely, constructs such as SI, FC, and PV were not significantly associated with IU. In the case of direct relationships, EE and FC have the greatest effects on IU and UN, respectively. Considering the moderating effects of age and using years, the empirical results suggested that age does not moderate the relationships proposed in this study. However, using years moderated the relationship between PE and IU as well as that between FC and IU. In terms of mediating effects, the results show that IU had significant and positive mediating effects on the connections among EE, HM, and UN. In summary, this study provides nuanced insights into the predictors of the acceptance of agricultural technology among small rural farmers. These results enhance our understanding of the factors associated with the adoption of new technologies in the agricultural sector and offer valuable implications for researchers, policymakers, and practitioners in the field.

Despite providing valuable insights, this study has certain limitations that should be acknowledged to contextualize the findings and guide future research. *First*, it does not explicitly consider external factors such as market trends, policy changes, or global events, which could influence technology adoption. Future research could incorporate a broader contextual analysis to better understand how external factors interact with the observed determinants. Second, the study relied on cross-sectional data, capturing a snapshot of respondents' perceptions and behaviors at a particular moment in time. This design limits the ability to establish causality and examine how variables interact over time. Additionally, the findings are specific to the context and time-frame of the data collection, meaning they may not fully reflect the broader or evolving trends in agriculture. Factors such as changes in economic conditions, policy interventions, or market dynamics could influence the behaviors and attitudes observed in this study. Consequently, the results should be interpreted with caution, considering the circumstances that prevailed during the data collection period. Future research, particularly longitudinal studies, would be valuable in providing a more comprehensive understanding of how these factors evolve and impact agricultural practices over time. *Third*, the data collected in the study were based on self-reported measures and using online questionnaire platform, introducing the possibility of common method bias. Respondents may provide socially desirable responses or exhibit consistency in their responses. The use of objective measures or a mixed-methods approach can enhance the robustness of findings. *Fourth*, this study may not account for all potential unobserved variables that could impact the relationships examined. Unobserved factors, such as cultural influences or contextual nuances specific to the agricultural domain, might influence the formation of behaviors related to technology adoption but are not explicitly addressed in this research.

Data availability

The original contributions presented in the study are included in the article/Supplementary Material (S2. Dataset—New Agricultural Technology), further inquiries can be directed to the corresponding author/s.

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Appendix A. Loading and cross loadings

	PE	EE	HM	SI	FC	PV	IU	UN
PE1	0.817	0.409	0.400	0.377	0.401	0.346	0.355	0.355
PE2	0.820	0.420	0.391	0.373	0.406	0.398	0.391	0.469
PE3	0.814	0.415	0.421	0.391	0.420	0.330	0.367	0.398
PE4	0.849	0.352	0.413	0.408	0.466	0.391	0.405	0.443
PE5	0.821	0.424	0.422	0.360	0.381	0.357	0.356	0.378
EE1	0.416	0.849	0.263	0.221	0.273	0.374	0.347	0.361
EE2	0.444	0.863	0.216	0.236	0.280	0.333	0.390	0.285
EE3	0.436	0.829	0.235	0.193	0.212	0.298	0.346	0.298
EE4	0.379	0.831	0.200	0.183	0.274	0.274	0.367	0.362
EE5	0.355	0.805	0.156	0.169	0.220	0.364	0.265	0.253
HM1	0.428	0.227	0.838	0.226	0.320	0.208	0.306	0.341
HM2	0.434	0.197	0.824	0.225	0.332	0.216	0.308	0.298
HM3	0.405	0.224	0.818	0.223	0.265	0.208	0.300	0.316
HM4	0.408	0.214	0.823	0.286	0.297	0.240	0.369	0.342
HM5	0.368	0.203	0.819	0.222	0.293	0.228	0.285	0.338
SI1	0.392	0.225	0.276	0.817	0.300	0.307	0.235	0.242
SI2	0.384	0.174	0.189	0.815	0.339	0.205	0.267	0.294
SI3	0.327	0.187	0.237	0.805	0.298	0.225	0.208	0.253
SI4	0.415	0.217	0.259	0.834	0.346	0.248	0.270	0.297
SI5	0.367	0.183	0.226	0.822	0.346	0.228	0.201	0.307
FC1	0.363	0.287	0.257	0.309	0.786	0.202	0.250	0.290
FC2	0.431	0.271	0.324	0.332	0.826	0.266	0.279	0.295
FC3	0.458	0.193	0.302	0.351	0.839	0.265	0.284	0.407
FC4	0.397	0.300	0.279	0.294	0.783	0.218	0.272	0.243
FC5	0.370	0.188	0.312	0.313	0.790	0.179	0.221	0.274
PV1	0.300	0.305	0.234	0.227	0.174	0.784	0.222	0.174
PV2	0.318	0.350	0.181	0.230	0.248	0.833	0.272	0.202
PV3	0.349	0.263	0.175	0.267	0.197	0.792	0.229	0.226
PV4	0.424	0.300	0.275	0.206	0.264	0.802	0.258	0.262
PV5	0.375	0.335	0.188	0.261	0.240	0.734	0.146	0.228
IU1	0.386	0.359	0.300	0.318	0.266	0.250	0.837	0.257
IU2	0.324	0.319	0.329	0.194	0.300	0.176	0.798	0.240
IU3	0.412	0.392	0.259	0.269	0.268	0.267	0.830	0.256
IU4	0.390	0.345	0.343	0.198	0.244	0.266	0.805	0.274
IU5	0.348	0.281	0.342	0.211	0.258	0.241	0.820	0.243
UN1	0.400	0.297	0.332	0.261	0.284	0.280	0.207	0.793
UN2	0.399	0.298	0.335	0.278	0.309	0.244	0.261	0.831
UN3	0.413	0.280	0.377	0.290	0.293	0.221	0.254	0.822
UN4	0.409	0.343	0.311	0.314	0.346	0.200	0.329	0.843
UN5	0.423	0.316	0.282	0.249	0.330	0.194	0.205	0.813

Source: Author's data analysis
PE Performance Expectancy, *EE* Effort Expectancy, *HM* Hedonic Motivation, *SI* Social Influence, *FC* Facilitating Conditions, *PV* Price Value, *IU* Intention to Use New agricultural technology, *UN* Usage of New agricultural technology.

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Author contributions

XZ, MM, and MMM: Conceptualization, Investigation, Methodology, Writing—Original Draft Preparation. AAlM and QY: Conceptualization, Methodology, Formal Analysis, Writing—Review & Editing.

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Competing interests

The authors declare no competing interests.

Ethics

The Nantong Institute of Technology's human research ethics committee approved this study (ID: BS-NIT-2023-0407) on April 24, 2023, under the condition that it be conducted with integrity, respect for life, and adherence to human rights. This study has been performed in accordance with the Declaration of Helsinki.

Informed consent

Written informed consent was obtained from all participants during the survey period, which spanned from May 2, 2023, to June 16, 2023, using an online survey form. The participation was wholly voluntary, without any risks, and did not involve any form of compensation. Participants provide their consent to publish, present and/or share the anonymous data.

Additional information

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