**Journal of Economics, Finance and Accounting Studies**
ISSN: 2709-0809
DOI: 10.32996/jefas
Journal Homepage: www.al-kindipublisher.com/index.php/jefas

JEFAS
AL-KINDI CENTER FOR RESEARCH AND DEVELOPMENT

**| RESEARCH ARTICLE**

# Willingness of Farmers to Adopt Blockchain Technology in Smart Agriculture

**Shang-Chuan Shih[1] ✉ and Bang-Han Chiu[2]**
[1]*PhD candidate at the College of Management, Yuan Ze University, Taiwan*
[2]*Director, Research Center for Smart Production & Innovation Management at Yuan Ze University, Taiwan*
**Corresponding Author:** Shang-Chuan Shih, **E-mail**: a7785313boat@gmail.com

**| ABSTRACT**

In order to achieve the SDGs, blockchain technology can potentially improve the sustainability of the agriculture ecosystem. Therefore, this research drawing a UTAUT extended model by the introduction of Perceived Value(PV), Government Support(GS) and Information Security(IS), explored the factors that influence farmers' intention to adopt Blockchain-A in Taiwan. First, the extended model has a stronger explanatory power, supplementing the technology acceptance theory. Second, the analysis shows PV, GS, and IS play mediating roles and clarifies the psychological mechanism affecting the adoption of Blockchain-A by farmers. Third, the results of this study provide a basis for policy suggestions that can help the government to formulate and promote appropriate sustainable agriculture policies.

**| KEYWORDS**

Blockchain-A, UTAUT, DLT

**| ARTICLE INFORMATION**

**ACCEPTED:** 04 August 2023 **PUBLISHED:** 08 August 2023 **DOI:** 10.32996/jefas.2023.5.4.3

## 1. Introduction

Commerce on the Internet has come to rely almost exclusively on financial institutions serving as trusted third parties to process electronic payments. The cost of mediation increases transaction costs(Nakamoto, 2008). Therefore, Distributed Ledger Technology(DLT) caused by blockchain will alleviate the agency problem and optimize the organizational operation process, thereby improving efficiency, reducing costs, and fundamentally changing the market structure(Catalini & Gans, 2020). For example, the traceability of blockchain will make accounting information more fully disclosed, hence expanding the market of products(Montecchi, Plangger, & Etter, 2019). The first realized case in the worldwide agriculture field is "Hegufang", which is a rice field located in Chishang Township, Taitung County, Taiwan. In early 2018, blockchain and IOT were introduced in "Hegufang", then the planting process, environmental data, ecological images, etc., were completely recorded in the blockchain system where the rice traceability was established. Made Taiwan high-quality rice marketing international.

In existing agriculture, sensors, satellites, and drones are often employed to collect data from farms which facilitates the forming of big data and deploying of IOT, and this helps optimize farm operations for the farmers(Maru et al., 2018). Ecological and environmental problems such as shortage of resources, intensified climate change, fierce competition in the international market, and excessive use of pesticides and fertilizers may lead to instability in the quantity and quality of crops and incur the shortage and uncertainty of food supply(Ho et al., 2018; van den Berg et al., 2020). Therefore, the Council of Agriculture in Taiwan(COA) continued to launch "New Agricultural Innovation Plan 2.0"during the time period from 2021 through 2024 by introducing sensors, smart devices, IOT and analytics of big data, initiating the construction of blockchain in agriculture(Blockchain-A).

Although DLTs in agriculture are still in their infancy, has attracted great attention from countries all over the world, especially countries with state-of-the-art (LIANG Xiaohe, ZHOU Ailian, XIE Nengfu, ZHANG Yi & WU Saisai, 2021). Accordingly, based on the theoretical framework of the Unified Theory of Acceptance and Use of Technology(UTAUT), this study incorporates Perceived Value(PV), Government Support(GS), and Information Security(IS) as the constructs of UTAUT. We employ this extended model to explore the farmers' acceptance of block chain in Taiwan. Through empirical investigation, we would find out the key factors that affect the willingness of farmers to adopt smart agricultural technology and then help digitally transform their operations so as to enhance the competitiveness of agricultural products in global markets.

## 2. Literature Review

### *2.1 Block chain in Smart Agriculture*

Chandan, John, and Potdar(2023) show the agri-food sector has one of the lowest rates of information technology penetration for innovation. In order to achieve the SDGs, blockchain can potentially improve the sustainability of the food supply chain by providing a transparent traceability system. Blockchain combined with IOT can help farmers to build a trusted, open, and environmentally friendly smart agricultural system(J. Lin, Shen, Zhang, & Chai, 2018), the Food and Agriculture Organization of the United Nations(UNFAO) published the report "E-agriculture in action: Blockchain for agriculture–Opportunities and Challenges" in 2019 on the prospect of blockchain application in agriculture, mentioning that blockchain can development agri-business. Aiming at this prospect, the "Smart Agriculture" project promoted by the COA is positioned as "Smart Production" and "Digital Services". Now consumers can see the “Odin Ding blockchain traceability certification QR Code”(Figure 1) on the fruits at the market in various countries. After scanning the code, consumers can read the whole growing history of agricultural products. Taking bananas as an example, the market price of bananas has long been in the state of throat-cutting in the international agricultural market for decades. In specific, the global quotation is, on average, 6 to 7 US dollars per box, but the average price of bananas grown in Taiwan is as high as $22 to $25. This can be attributed to the guarantee of high quality so that international consumers are willing to buy at a much higher price.


Figure 1. Blockchain-A QR Code
Source: https://meet.bnext.com.tw/articles/view/44948

While blockchain can enable transparent food supply chains, there still exist many obstacles and challenges, and these challenges involve improvement in technology, education, policy and regulatory framework. And further research is needed.

### *2.2 UTAUT and Research Hypotheses*

Venkatesh, Morris, Davis, and Davis(2003) first proposed the Unified Theory of Acceptance and Use of Technology(UTAUT), which is widely used to explore the acceptance of IOT, communications and others in agriculture. The UTAUT has a positive explanatory power for the intention of smart agricultural users(Ena & Siewa; Xie et al., 2022). In addition, among the 902 research papers on blockchain from 2010 to 2021, only 3 papers conduct empirical investigation on agriculture-related topics, and none of them adopt UTAUT. The main obstacles to the adoption of blockchain include "Security and privacy risks ", "Cost", "Organizational Policy ", etc., suggesting the demand for further research(AlShamsi et al., 2022). Accordingly, to fill the research gap, this study takes PV, GS and IS as mediators to construct the extended model.

First of all, in order to investigate the relationship between UTAUT and smart agriculture, operational definitions of Performance Expectations(PE), Effort Expectation(EE), Social Influence(SI), and Facilitating Conditions(FC) as follows: (1)PE: Farmers believe that Blockchain-A can help agricultural management and added market value. (2)EE::Farmers believe the effort cost required to Blockchain-A when they believe that learning is relatively simple and easy, they will be to adopt it. (3)SI: The views and practices of surrounding farmers and farmers' associations influence farmers to adopt Blockchain-A. (4)FC: The level of support that farmers feel for Blockchain-A 's establishment, discounts and services.
The following hypotheses are proposed:

**H1: The UTAUT factors positively affect the intention to use Blockchain-A.**

Kaske, Mvena, and Sife(2018) showed the use of Blockchain-A reduces information costs, thereby facilitating farmers to enter the market and obtain financial support. Rocha, de Oliveira, and Talamini(2021) showed that this technology is in the agricultural supply chain. It is in the early experimental stage, but if it can be put into practice, it will be profitable.

When farmers believe that the use of Blockchain-A will generate higher income, the willingness to adopt this technology will be greater. Therefore, PV exerts a major impact on the application of new smart agricultural technologies(Xiang & Gao, 2023). However, some studies show that the influence of PV is not significant for the willingness to use smart agriculture(Kang, Chang, Lee, & Jeong, 2020), while some other studies show that PV exerts a negative impact for farmers to use smart agriculture(Pillai & Sivathanu, 2020). In order to understand the psychological mechanism of farmers, this study in-depth interviews senior professionals in the field of agriculture referred to Xie et al. (2022) and Zia et al. (2022). PV is introduced into the UTAUT model as a mediating variable, and the following hypotheses are proposed:

**H2: PV positively affects intention to use Blockchain-A.**
**H2A: PV plays a mediating role between UTAUT and BI.**

According to the 2019 report by UNFAO, more than 820 million people around the world live in hunger. Governments play a pivotal role in solving food shortages, can reduce food fraud, improve food safety, and increase income(De Clercq, Vats, & Biel, 2018). Blockchain is complex; potential change will take time and good governance to gain trust and widespread adoption(Maru et al., 2018).

Park, Lee, and Yi(2011) showed that the UTAUT theory did not consider the joint impact of group-level variables on individual acceptance because organizational support will have a significant impact on individuals' use intentions. At the same time, looking back at 2003-2014, there are 1,267 articles related to UTAUT have been published, which still do not take into account the differences in the attributes of individuals and organizations, and include cross-domain dimensions such as "Organization and Environment Factors(EV)"(Venkatesh, Thong, & Xu, 2016). However, Giua, Materia, and Camanzi(2022) show organizational matching conditions directly affect decisions rather than usage intentions.

Governments have various roles in blockchain adoption to solve many legal, regulatory, ethical, and technical barriers(Ojo & Adebayo, 2017). For farmers, supply chain members need to store and process traceability-related information to provide proof of compliance to national authorities(Casino, Kanakaris, Dasaklis, Moschuris, & Rachaniotis, 2019). In summary, the operational definition of GS: Top government agencies' guidance and budgeting for the establishment and use of Blockchain-A in smart agricultural ecosystems.

In addition, UNFAO recommends the integration of Information and Communication Technology(ICT) electronic agricultural infrastructure and blockchain for agricultural, environmental data, personnel management and other records, and its data integrity can be guaranteed(Y. -P. Lin et al., 2017). Bermeo-Almeida et al.(2018) also show 10 of the 5 studies of Blockchain-A were designed to address issues related to privacy and security. However, Kamilaris et al.(2019) suggested that while blockchain ensures transparency and helps build trust, it does not protect user privacy, which is especially important in a food supply ecosystem where many players compete with each other. Therefore, maintaining a certain level of privacy is an existing challenge of blockchain. Pearson et al.(2019) also suggested that permanent data visibility may jeopardize privacy concerns and may eventually strengthen the monitoring capabilities of centralized entities.

In summary, this study incorporated GS and IS into EV. Furthermore, in order to understand the psychological mechanism of farmers, EV is introduced into the UTAUT model as a mediating variable; the following hypotheses are proposed:

**H3: EV positively affects intention to use Blockchain-A.**
**H3A: EV plays a mediating role between UTAUT and BI.**

## 3. The Research Model

### *3.1. Research model*

Figure 2 shows the conceptual framework of this study, and the presented hypotheses were tested using Structural Equation Modeling (SEM).

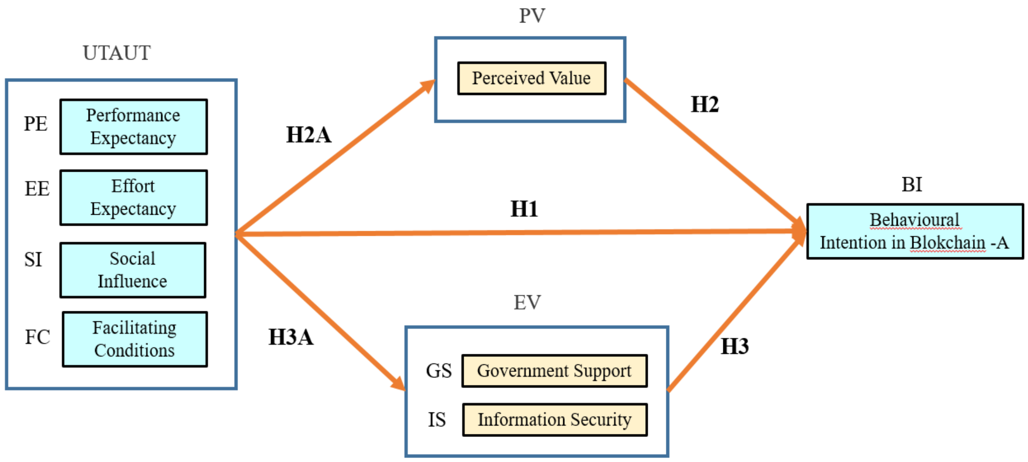


Figure 2. Research model

### *3.2. Sampling Subjects and Methods*

From August to December 2022, face-to-face surveys interviewed experienced farmers(more than 20 years), specialists (Taiwan Agriculture Research Institute), professors of agriculture(Chung Hsing University) and reviewed by scholars to establish construct and content validities. The 5-point Likert scale was used; a high score indicated strong agreement with an item.

This research adopts the method of an online questionnaire survey to collect data. The questionnaire was set up on the SurveyCake; the link was sent to the subjects who meet the survey qualifications of this research: (1)The occupation is farmers. (2)Have more than 1 "point" of land(1 "point"=9.69917ares). (3)Planting and farm management experience. Those who complete the questionnaire can get Line Points rewards equivalent to cash.

From January 3 to January 10, 2023, the questionnaire IP address is recorded. The same IP cannot be filled in repeatedly. A total of 485 questionnaires were collected in this study, 42 invalid questionnaires were excluded, and 443 were valid questionnaires. The recovery rate was 91.34%. To better understand the characteristics of respondents, a demographic analysis was carried out, with the descriptive statistics of the sample being gathered afterwards.

## 4. Empirical Analysis

### *4.1. Descriptive Statistics*

A total of 443 valid questionnaires were received in this study, of which males accounted for 54%, and females accounted for 46%. The ages were mainly young people(25-44 years old) and middle-aged people(45-59 years old), accounting for 35.4% and 57.8%, respectively, according to the "Republic of China Population Estimation(2022-2070)" of the National Development Commission in August 2022, the proportion of the total population aged 15-64 will be reduced from 70.7% to 47.8%. For job undertakers, the gap in the agricultural grassroots labor force is gradually expanding. COA calls for smart agricultural innovation and industrial transformation. The agricultural seniority is mainly 6-10 years and 11-15 years, accounting for 30.2% and 50.3%, respectively. The cultivated area is mainly 2-10 "points", accounting for 90.7%. Those who have taken courses related to smart agriculture account for 78.8%(Table 1).

Table 1. Descriptive Statistics

| Variable | Definition | Frequency(n) | Proportion(%) |
|---|---|---|---|
| Gender | male | 239 | 54.0 |
| | female | 204 | 46.0 |
| Age | 15-24 years | 9 | 2.0 |
| | 25-44 years | 157 | 35.4 |
| | 45-59 years | 256 | 57.8 |
| | 60-74 years | 19 | 4.3 |
| | Older than 75 years | 2 | 0.5 |
| Agricultural seniority | under 5 years | 14 | 3.2 |
| | 6-10 years | 134 | 30.2 |
| | 11-15 years | 223 | 50.3 |
| | 16-20 years | 48 | 10.8 |
| | 21-25 years | 15 | 3.4 |
| | 26+ years | 9 | 2.0 |
| Cultivated area | within 2 points* | 176 | 39.7 |
| | 2 points - 5 points | 125 | 28.2 |
| | 5 points -10 points | 101 | 22.8 |
| | 10 points or more | 41 | 9.2 |
| Attended courses related to smart agriculture | have | 349 | 78.8 |
| | none | 94 | 21.2 |

Note : *1 "point" = 9.69917ares

### *4.2 Confirmatory Factor Analysis*

The Cronbach's α value of each construct is between 0.804 and 0.888(Table 2), both of which are greater than 0.7(Nunnally, 1978). This study employed a two-step modeling approach(Aderson & Gerbing, 1988). The marida coefficient is 7.904<30*(30+2)=960, so the model uses the maximum likelihood estimation method(Bollen, 1989). In addition, the standard errors(SE) of the factor loadings of all items are between 0.186 and 0.21, and they are all significant. The standardized regression coefficient(Standardized Factor Loading, SFL) are between 0.720 and 0.844; there is no situation that exceeds or is too close to 1(>0.95)(Huang Fangming, 2015). As a result, it was regarded as appropriate.

Table 2. Confirmatory Factor Analysis

| Variable | Item | Mean (M) | Standard Deviation (SD) | SE | SFL | CA (α) | CR | AVE | Reliability/Validity Criteria |
|---|---|---|---|---|---|---|---|---|---|
| Performance Expectancy | PE1 | 3.83 | 1.034 | 0.19* | 0.818 | 0.863 | 0.863 | 0.612 | using |
| | PE2 | 3.76 | 1.044 | 0.198* | 0.763 | | | | |
| | PE3 | 3.75 | 1.031 | 0.195* | 0.768 | | | | |
| | PE4 | 3.78 | 1.080 | 0.202* | 0.780 | | | | |
| Effort Expectancy | EE1 | 3.77 | 1.017 | 0.196* | 0.742 | 0.852 | 0.853 | 0.592 | using |
| | EE2 | 3.76 | 1.057 | 0.197* | 0.800 | | | | |
| | EE3 | 3.72 | 1.018 | 0.195* | 0.748 | | | | |
| | EE4 | 3.79 | 1.032 | 0.194* | 0.784 | | | | |
| Social Influence | SI1 | 3.81 | 1.045 | 0.206* | 0.761 | 0.808 | 0.809 | 0.585 | using |
| | SI2 | 3.78 | 1.043 | 0.208* | 0.749 | | | | |
| | SI3 | 3.76 | 1.035 | 0.203* | 0.784 | | | | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Facilitating Conditions | FC1 | 3.77 | 1.027 | 0.19* | 0.801 | 0.868 | 0.868 | 0.622 | using |
| | FC2 | 3.75 | 1.083 | 0.202* | 0.785 | | | | |
| | FC3 | 3.77 | 1.040 | 0.193* | 0.791 | | | | |
| | FC4 | 3.78 | 1.062 | 0.199* | 0.777 | | | | |
| Perceived Value | PV1 | 3.86 | 1.017 | 0.204* | 0.722 | 0.823 | 0.823 | 0.538 | using |
| | PV2 | 3.90 | 0.926 | 0.186* | 0.720 | | | | |
| | PV3 | 3.90 | 0.960 | 0.191* | 0.740 | | | | |
| | PV4 | 3.88 | 0.969 | 0.192* | 0.752 | | | | |
| Government Support | GS1 | 3.85 | 1.087 | 0.2* | 0.814 | 0.872 | 0.873 | 0.633 | using |
| | GS2 | 3.76 | 1.135 | 0.205* | 0.844 | | | | |
| | GS3 | 3.74 | 1.044 | 0.201* | 0.729 | | | | |
| | GS4 | 3.73 | 1.058 | 0.197* | 0.790 | | | | |
| Information Security | IS1 | 3.74 | 1.134 | 0.207* | 0.810 | 0.888 | 0.889 | 0.666 | using |
| | IS2 | 3.70 | 1.105 | 0.201* | 0.819 | | | | |
| | IS3 | 3.77 | 1.103 | 0.199* | 0.829 | | | | |
| | IS4 | 3.73 | 1.094 | 0.2* | 0.806 | | | | |
| Behavioral Intention | BI1 | 3.74 | 0.957 | 0.195* | 0.756 | 0.804 | 0.805 | 0.579 | using |
| | BI2 | 3.72 | 1.032 | 0.21* | 0.752 | | | | |
| | BI3 | 3.73 | 1.031 | 0.209* | 0.775 | | | | |

Note 1 : * represents P< 0.05.

Note 2: SE, which is Error Variance; SFL, which is Standardized Factor Loadings; CA, which is Cronbach's alpha coefficient; CR, which is Component reliability and AVE, which is Average Variance Extracted.

Table 2 shows the component reliability(CR) of each facet is higher than 0.6, and the AVE is between 0.538 and 0.666, both exceeding 0.5(Fornell & Larcker, 1981). Figure 3 shows the CMIN/DF=1.094, GFI=0.943, AGFI=0.930, CFI=0.994, RMR=0.034, which meet the standards.

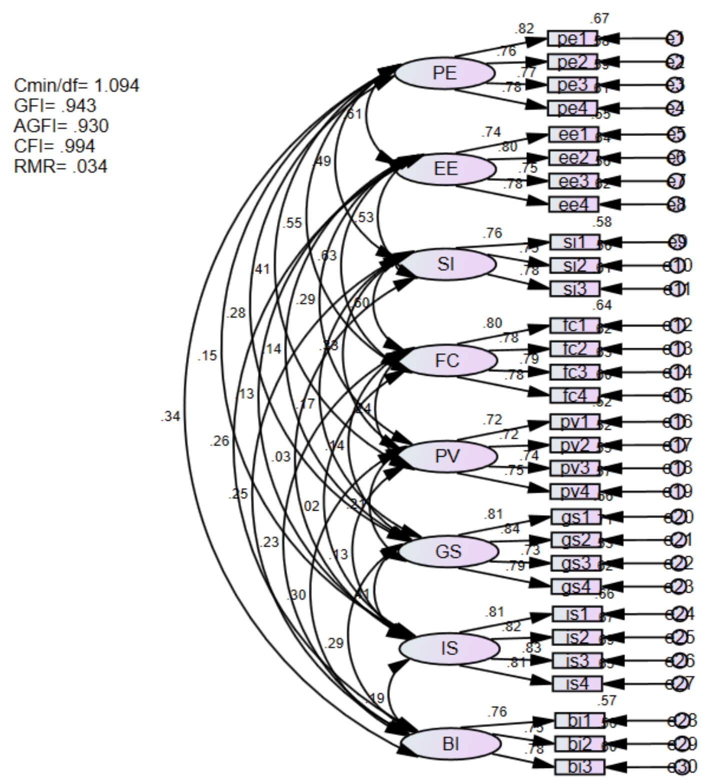


Figure 3. Results of the measurement model

Table 3 shows the square root of AVE is between 0.734 and 0.816, was greater than 0.70 in all cases and greater than the square of the correlations(Hair, Andreson, Tatham, & Black, 1998), thus suggesting discriminant validity.

Table 3. Correlation coefficient matrix of each construct

| | PE | EE | SI | FC | PV | EV | BI |
|---|---|---|---|---|---|---|---|
| PE | 0.783 | | | | | | |
| EE | 0.613 | 0.769 | | | | | |
| SI | 0.489 | 0.528 | 0.765 | | | | |
| FC | 0.546 | 0.629 | 0.602 | 0.788 | | | |
| PV | 0.407 | 0.294 | 0.334 | 0.240 | 0.734 | | |
| EV | 0.282 | 0.143 | 0.173 | 0.138 | 0.207 | 0.795 | |
| BI | 0.148 | 0.127 | 0.033 | 0.021 | 0.127 | 0.410 | 0.816 |

Note1: The diagonal bold italic values are the square roots of AVE

Note1: PE: Performance Expectancy; EE: Effort Expectancy; SI: Social Influence; FC: Facilitating Conditions; FC: Facilitating Conditions; PV: Perceived Value; EV: Organization and Environment Factors; BI: Behavioral Intention, the same below.

We used the bootstrap method, and repeated sampling was set to 1,000 times. Table 4 shows the 95% confidence intervals of the correlation coefficients for each construct do not contain 1(Torkzadeh, Koufteros, & Pflughoeft, 2003), thus suggesting discriminant validity.

Table 4. Confidence interval test

**Covariances: (Group number 1 - Default model)**

| Parameter | | | Estimate | Lower | Upper | P |
|---|---|---|---|---|---|---|
| PE | <--> | EE | .031 | .026 | .034 | .002 |
| PE | <--> | SI | .024 | .019 | .029 | .001 |
| PE | <--> | FC | .027 | .023 | .031 | .002 |
| PE | <--> | PV | .020 | .014 | .026 | .002 |
| PE | <--> | GS | .014 | .008 | .020 | .002 |
| PE | <--> | IS | .007 | .002 | .012 | .004 |
| PE | <--> | BI | .017 | .011 | .022 | .003 |
| EE | <--> | SI | .026 | .021 | .031 | .002 |
| EE | <--> | FC | .031 | .027 | .035 | .002 |
| EE | <--> | PV | .015 | .009 | .021 | .002 |
| EE | <--> | GS | .007 | .001 | .012 | .014 |
| EE | <--> | IS | .006 | .001 | .012 | .022 |
| EE | <--> | BI | .013 | .007 | .019 | .003 |
| SI | <--> | FC | .030 | .025 | .034 | .003 |
| SI | <--> | PV | .017 | .011 | .023 | .002 |
| SI | <--> | GS | .009 | .003 | .014 | .004 |
| SI | <--> | IS | .002 | -.004 | .007 | .552 |
| SI | <--> | BI | .013 | .007 | .018 | .003 |
| FC | <--> | PV | .012 | .006 | .018 | .002 |
| FC | <--> | GS | .007 | .002 | .012 | .012 |
| FC | <--> | IS | .001 | -.004 | .006 | .724 |
| FC | <--> | BI | .011 | .005 | .018 | .002 |
| PV | <--> | GS | .010 | .005 | .016 | .001 |
| PV | <--> | IS | .006 | .000 | .012 | .039 |
| PV | <--> | BI | .015 | .009 | .021 | .002 |
| GS | <--> | IS | .020 | .015 | .025 | .002 |
| GS | <--> | BI | .015 | .009 | .020 | .002 |
| IS | <--> | BI | .010 | .004 | .015 | .003 |

### *4.3. Hypothetical Path Testing*

After assessing the measurement model, a structural model or path analysis is carried out. Firstly, the model is shown in Figure 4. The hypotheses H1, H2, H3 are accepted(Table 5).

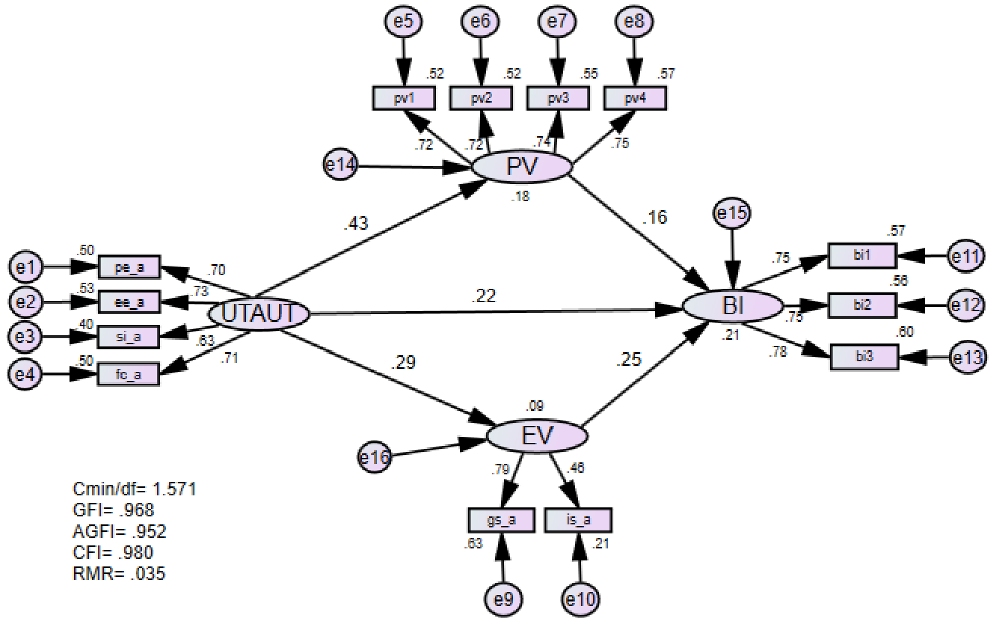


Figure 4. Results of path analysis

Table 5. Path coefficients

| Path | Unnormalized Estimates | Normalized Estimates | 95% Confidence Interval | | p | Decision |
|---|---|---|---|---|---|---|
| | | | Lower Bounds | Upper Bounds | | |
| UTAUT →PV | 0.471 | 0.426* | 0.305 | 0.546 | 0.002 | |
| PV → BI | 0.159 | 0.157* | 0.015 | 0.283 | 0.034 | H2 Accept |
| UTAUT → BI | 0.249 | 0.222* | 0.054 | 0.377 | 0.004 | H1 Accept |
| UTAUT →EV | 0.305 | 0.292* | 0.147 | 0.446 | 0.001 | |
| EV →BI | 0.271 | 0.252* | 0.089 | 0.424 | 0.004 | H3 Accept |

Note : * represents P< 0.05.

We employed a parallel multiple-mediation approach to justify the influencing mechanism of Blockchain-A on farmers' intentions. Sobel test has limitations(Hayes, 2009), and Cheung(2007) proposed the mediating effect and the sample size were both small. The bootstrap CI and likelihood-based CI were preferred over the Wald CI. As shown in Table 6, the hypotheses H2A and H3A are accepted. The overall effect is 0.362, greater than the direct effect is 0.222, showing the extended model has greater explanatory power.

Table 6. Parallel multiple mediation analysis(bootstrapping)

| Path | Unnormalized estimates | Normalized Estimates | 95% Confidence Interval | | p | Decision |
|---|---|---|---|---|---|---|
| | | | Lower Bounds | Upper Bounds | | |
| Indirect Effect | | | | | | |
| UTAUT→PV→BI | 0.075 | 0.067* | 0.012 | 0.131 | 0.026 | H2A Accept |
| UTAUT→EV→BI | 0.083 | 0.074* | 0.025 | 0.158 | 0.001 | H3A Accept |
| Direct Effect | | | | | | |
| UTAUT→BI | 0.249 | **0.222*** | 0.056 | 0.384 | 0.009 | |
| Overall Effect | | | | | | |
| UTAUT→BI | 0.407 | **0.362*** | 0.233 | 0.485 | 0.001 | |

Note : * represents P< 0.05.

## 5. Conclusion

Drawing on a UTAUT model extended by the introduction of PV, GS and IS, this study explored the factors that influence farmers' intention to adopt Blockchain-A. The analysis shows that PE, EE, SI, FC, PV, GS, and IS had significant positive effects on the intention to adopt. PV, GS, and IS played a partial mediating role, and the extended model had a stronger explanatory power than the original model. This supplemented the technology acceptance theory but also concluded that the expected profit, government policy, and information security is the problem of the most concern for farmers.

This study makes three main contributions. First, the research findings on the factors that influence the behavioral intention of farmers to adopt Blockchain-A enrich the theoretical support in the field of farm management and provide suggestions and references for the in-depth promotion of Blockchain-A. Second, the introduction of PV, GS, and IS as mediating variables in the UTAUT framework provides a theoretical model that clarifies the psychological mechanism affecting the adoption of Blockchain-A by farmers. Third, the results of this study provide a basis for policy suggestions that can help the government to formulate and promote appropriate ecological transformation policies.

In addition, this study has two limitations that should be noted. First, PV, in the same way as previous research in the area, focused on perceived gain and neglected perceived loss. It is undeniable that future research should include perceived loss to obtain a more systematic model. Second, the demographic characteristics of the participants in this study are not fully representative of farmers. Future research should seek to improve the generalizability of the findings by expanding the sample collection.

In the face of the global natural disasters brought about by climate change, the large enterprise has set a Net Zero goal, and before they fail to achieve this goal, they need to offset their own carbon dioxide emissions by providing funds to the carbon compensation mechanism. How to obtain carbon credits? In addition to purchasing from countries or companies, it can also be obtained by reducing existing carbon dioxide. Among them, "planting" is a very potential way to be carbon negative. At present, American agricultural technology companies Nori LLC has begun to sell carbon credits generated when farmers farm, but there is still a lack of fair and objective measurement mechanisms. Our suggestion for future research on their willingness to adopt blockchain.

**Funding:** This research received no external funding.
**Conflicts of Interest:** The authors declare no conflict of interest.
**Publisher's Note**: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers.

## References


[1] AlShamsi, M., Al-Emran, M., & Shaalan, K.(2022). A Systematic Review on Blockchain Adoption. *Applied Sciences, 12(*9), 4245.

[2] Anderson, JC, & Gerbing, DW(1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological bulletin, 103(*3), 411.

[3] Bermeo-Almeida, O., Cardenas-Rodriguez, M., Samaniego-Cobo, T., Ferruzola-Gómez, E., Cabezas-Cabezas, R., & Bazán-Vera, W. (2018). Blockchain in agriculture: A systematic literature review. Paper presented at the International Conference on Technologies and Innovation.

[4] Bollen, KA(1989). Structural equations with latent variables(Vol. 210): John Wiley & Sons.

[5] Casino, F., Kanakaris, V., Dasaklis, TK, Moschuris, S., & Rachaniotis, NP(2019). Modeling food supply chain traceability based on blockchain technology. *Ifac-Papersonline*, 52(13), 2728-2733.

[6] Catalini, C., & Gans, J. S. (2020). Some simple economics of the blockchain. *Communications of the ACM*, 63(7), 80-90.

[7] Chandan, A., John, M., & Potdar, V. (2023). Achieving UN SDGs in Food Supply Chain Using Blockchain Technology. *Sustainability*, 15(3), 2109.

[8] Cheung, MW (2007). Comparison of approaches to constructing confidence intervals for mediating effects using structural equation models. *Structural equation modeling: a multidisciplinary journal, 14(*2), 227-246.

[9] De Clercq, M., Vats, A., & Biel, A.(2018). Agriculture 4.0: The future of farming technology. *Proceedings of the World Government Summit, Dubai, UAE,* 11-13.

[10] Ena, GWW, & Siewa, ALS Factors Influencing the Behavioral Intention for Smart Farming in Sarawak, Malaysia. *Journal of Agribusiness, 9(*1), 37-56.

[11] Fornell, C., & Larcker, DF(1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research, 18(*1), 39-50.

[12] Giua, C., Materia, VC, & Camanzi, L.(2022). Smart farming technologies adoption: Which factors play a role in the digital transition? *Technology in Society, 68,* 101869.

[13] Hair, J., Andreson, R., Tatham, R., & Black, W.(1998). Multivariate data analysis. 5th(ed) Prentice-Hall Inc. Unites States of America.

[14] Hayes, AF(2009). Beyond Baron and Kenny: Statistical mediation analysis in the new millennium. *Communication monographs, 76(*4), 408-420.

[15] Ho, C.-H., Lur, H.-S., Yao, M.-H., Liao, F.-C., Lin, Y.-T., Yagi, N., & Lu, H. -J.(2018). The impact on food security and future adaptation under climate variation: a case study of Taiwan's agriculture and fisheries. *Mitigation and adaptation strategies for global change, 23,* 311-347.

[16] Huang Fangming(2015). Structural Equation Modeling-Theory and Application: Taiwan Wunan Book Publishing Co., Ltd.

[17] Kamilaris, A., Fonts, A., & Prenafeta-Boldύ, FX(2019). The rise of blockchain technology in agriculture and food supply chains. *Trends in Food Science & Technology, 91,* 640-652.

[18] Kang, D.-B., Chang, K.-J., Lee, Y.-K., & Jeong, M.-U.(2020). A study on the effects of changes in smart farm introduction conditions on willingness to accept agriculture-application of extended UTAUT model. *Korean Journal of Organic Agriculture, 28(*2), 119-138.

[19] Kaske, D., Mvena, ZSK, & Sife, AS(2018). Mobile phone usage for accessing agricultural information in Southern Ethiopia. *Journal of agricultural & food information, 19(*3), 284-298.

[20] LIANG Xiaohe, ZHOU Ailian, XIE Nengfu, ZHANG Yi & WU Saisai. (2021). Application Status and Technology Hotspots of Blockchain in Agriculture. *Journal of Agricultural Science and Technology, 23(*12), 84-93.

[21] Lin, J., Shen, Z., Zhang, A., & Chai, Y.(2018). Blockchain and IoT based food traceability for smart agriculture. Paper presented at the Proceedings of the 3rd international conference on crowd science and engineering.

[22] Lin, Y.-P., Petway, JR, Anthony, J., Mukhtar, H., Liao, S.-W., Chou, C.-F., & Ho, Y.-F.(2017). Blockchain: The evolutionary next step for ICT e-agriculture. *Environments, 4(*3), 50.

[23] Maru, A., Berne, D., De Beer, J., Ballantyne, P., Pesce, V., Kalyesubula, S.,... Chaves, J.(2018). Digital and data-driven agriculture: Harnessing the power of data for smallholders. *F1000 Research, 7(*525), 525.

[24] Montecchi, M., Plangger, K., & Etter, M.(2019). It's real, trust me! Establishing supply chain provenance using blockchain. *Business Horizons, 62(*3), 283-293.

[25] Nakamoto, S.(2008). Bitcoin: A peer-to-peer electronic cash system. Retrieved from https://bitcoin.org/bitcoin.pdf

[26] Ojo, A., & Adebayo, S.(2017). Blockchain as a next generation government information infrastructure: A review of initiatives in D5 countries. Government *3.0–Next Generation Government Technology Infrastructure and Services: Roadmaps, Enabling Technologies & Challenges,* 283 - 298.

[27] Park, S.-H., Lee, L., & Yi, MY(2011). Group-level effects of facilitating conditions on individual acceptance of information systems. *Information technology and management, 12(*4), 315-334.

[28] Pearson, S., May, D., Leontidis, G., Swainson, M., Brewer, S., Bidaut, L.,... Zisman, A.(2019). Are distributed ledger technologies the panacea for food traceability? *Global food security, 20,* 145-149.

[29] Pillai, R., & Sivathanu, B.(2020). Adoption of the internet of things(IoT) in the agriculture industry deploying the BRT framework. *Benchmarking: An International Journal,* 1341-1368.

[30] Rocha, G. d. SR, de Oliveira, L., & Talamini, E.(2021). Blockchain applications in agribusiness: A systematic review. *Future Internet, 13(*4), 95.

[31] Torkzadeh, G., Koufteros, X., & Pflughoeft, K.(2003). Confirmatory analysis of computer self-efficacy. *Structural Equation Modeling, 10(*2), 263-275.

[32] Tsai, T.-C.(2019). A Study of Law and Regulation on Agricultural Information Safety. *Hwa Kang Law Review, 67,* 85-140. doi:10.6868/HKLR.201912_(67).03

[33] van den Berg, H., Gu, B., Grenier, B., Kohlschmid, E., Al-Eryani, S., da Silva Bezerra, HS,... Velayudhan, R.(2020). Pesticide lifecycle management in Agriculture and public health: Where are the gaps? *Science of the Total Environment, 742,* 140598.

[34] Venkatesh, V., Morris, MG, Davis, GB, & Davis, FD(2003). User acceptance of information technology: Toward a unified view. *MIS quarterly,* 425-478.

[35] Venkatesh, V., Thong, JY, & Xu, X.(2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the association for Information Systems, 17(*5), 328-376.
[36] Xiang, W., & Gao, J.(2023). Do Not Be Anticlimactic: Farmers' Behavior in the Sustainable Application of Green Agricultural Technology—A Perceived Value and Government Support Perspective. *Agriculture*, 13(2), *247*.
[37] Xie, K., Zhu, Y., Ma, Y., Chen, Y., Chen, S., & Chen, Z.(2022). Willingness of Tea Farmers to Adopt Ecological Agriculture Techniques Based on the UTAUT Extended Model. *International Journal of Environmental Research and Public Health, 19(*22), 15351.
[38] Zia, A., Alzahrani, M., Alomari, A., & AlGhamdi, F.(2022). Investigating the Drivers of Sustainable Consumption and Their Impact on Online Purchase Intentions for Agricultural Products. *Sustainability*, 14(11), *6563*.