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Article

Blockchain adoption factors in agricultural supply chains: A PLS-SEM study

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Abstract: The purpose of this study is to explore factors influencing the blockchain adoption in agricultural supply chains, to make a particular focus on how security and privacy considerations, policy support, and management support impact the blockchain adoption intention. it further investigates perceived usefulness as a mediating variable that potentially amplifies the effects of these factors on blockchain adoption intention, and sets perceived cost as a moderating variable to test its influence on the strength and direction of the relationship between perceived usefulness and adoption intention. through embedding the cost-benefit theory into the integrated tam-toe framework and utilizing the partial least squares structural equation modeling (PLS-SEM) method, this study identifies the pivotal factors that drive or impede blockchain adoption in the agricultural supply chains, which fills the gap of the relatively insufficient research on the blockchain adoption in agriculture field. the results further provide empirical evidence and strategic insights that can guide practical implementations, to equip stakeholders or practitioners with the necessary knowledge to navigate the complexities of integrating cutting-edge technologies into traditional agricultural operations, thereby promoting more efficient, transparent, and resilient agricultural supply chains.

Keywords: blockchain technology; agricultural supply chain; PLS-SEM; TAM-TOE framework; perceived cost; perceived usefulness

1. Introduction

The agricultural supply chain (ASC) encompasses all stages from the farm to the table, involving planting, harvesting, processing, storing, transporting and selling (Bhat et al., 2021). It is a pillar for the sustainable and stable development of the national economy (Shen et al., 2022). The operation of the ASC resembles a systematic network, incorporating multiple stakeholders such as farmers, intermediaries, processors, and retailers, forming a comprehensive, multi-layered, and diversified agricultural product supply chain system (Luo et al., 2018). Due to its complexity, reliance on climatic conditions, and the perishable nature of agricultural products, the current ASC faces significant challenges, including inefficiency, lack of transparency, food safety issues, high market volatility, and insufficient regulation. Inefficient logistics, information asymmetry among stakeholders, lack of consumer trust in food safety, and opaque regulatory rules severely impact daily life and constrain the high-quality development of agricultural modernization (Skalkos, 2023; Zhong et al., 2023).

Blockchain technology (BT), as a decentralized distributed ledger, exhibits a number of distinctive characteristics, including encrypted timestamps, irreversibility, immutability, auditability, persistency, and consensus mechanisms. These attributes have the potential to address the aforementioned challenges (Sillaber and Treiblmaier, 2021). Panwar et al. (2023) affirmed the significant role of BT in enhancing trust, efficiency, and traceability in agriculture. Zhan and Wan (2024) identified risk control capabilities, quality safety inspections, and smart contract constraints of BT as significant pathways influencing quality safety credit regulation. The practical applications of blockchain in agricultural supply chains (ASCs) are becoming increasingly evident. Walmart, Nestlé, Dole, Golden Foods, and eight other suppliers collaborated with IBM to integrate IBM's blockchain platform into their supply chains (Xiong et al., 2020). The introduction of BT by Farmers Edge has facilitated operations for both producers and consumers in agricultural applications (Alobid et al., 2022). Furthermore, government departments are actively promoting the application of BT in agriculture. China's No. 1 Central Document had emphasized integrating BT application with agricultural practices for two consecutive years.

Nevertheless, despite the support expressed by scholars, practitioners, and governments, the actual adoption of BT has not met expectations. Gartner forecasts that by 2025, 90% of blockchain projects will remain in the proof-of-concept phase (Catalini, 2017). Even years after the introduction of Bitcoin, blockchain applications outside of finance remain limited to a few pilot projects (Varma, 2019). Markus and Buijs (2022) posit that the application of blockchain in supply chains is not widespread and that further time and effort are required to achieve a mature integration. In a review of the application of BT in food sectors, Xiong et al. (2020) found that blockchain in food supply chains is still in its early stages, with numerous immature and imperfect aspects during implementation. The application of blockchain in ASCs is still in its infancy, with numerous issues and uncertainties that need to be resolved before it can be widely adopted (Jahanbin et al., 2023).

In light of the considerable obstacles to blockchain adoption, numerous scholars have commenced into the underlying causes. Ganguly (2024) classified the factors identified from literature and interviews following Technology-Organization-Environment (TOE) framework, thereby determining the technical, organizational, and environmental challenges faced by logistics supply chains in adopting BT. In their review of BT in food supply chains, Astuti and Hidayati (2023) identified financial constraints, human resources, and policy changes as key obstacles. Dehghani et al. (2022) employed a case study to propose a framework for the adoption challenges of BT in halal food SMEs. Tsai et al. (2023) utilized DEMATEL to highlight issues like lack of government regulation and resource requirements. Meanwhile, Zheng et al. (2023) employed game theory to assess how costs and government policies influence the decision-making processes related to blockchain implementation in agriculture. Therefore, it is evident that most research relies on reviews, case studies, textual analysis, DEMATEL, game theory, or other conceptual analysis. There is a lack of comprehensive empirical research based on actual data analysis (Chiaraluce et al., 2024).

This study aims to fill this gap by following the TOE framework, which primarily evaluates the factors influencing information technology adoption from an organizational perspective (Forrest, 1991), to explore the reasons behind the slow adoption of this promising technology in ASCs. The study identifies three critical factors relevant to the context under investigation: security and privacy (technological dimension), management support (organizational dimension), and policy support (environmental dimension). It is crucial to consider the role of individual perceptions, particularly the perceived usefulness of the technology in question, as these perceptions held by management can significantly influence decision-making processes (Davis, 1989; Pugh, 1966). Furthermore, the cost-benefit analysis theory posits that perceived cost is a pivotal factor that organizations take into account when making decisions (Layard and Glaister, 1994; Lin, 2014).

The following five research questions are proposed: 1) What is the relationship between security and privacy and blockchain adoption intention in ASCs? 2) What is the relationship between management support and blockchain adoption intention in ASCs? 3) What is the relationship between policy support and blockchain adoption intention in ASCs? 4) Does the perceived usefulness have mediating effect between these factors and blockchain adoption intention in ASCs? 5) Does the perceived cost moderate the relationship between perceived usefulness and blockchain adoption intention in ASCs?

This study extends the integrated TAM-TOE framework within the context of ASCs by addressing these questions and providing a more comprehensive theoretical perspective through incorporating the perceived cost variable. Furthermore, the explicit delineation of pivotal impediments provides novel insights and recommendations for policymakers and practitioners regarding the BT application. The following sections are organized as follows: Section 2 presents a literature review, summarizing previous research and variables, and proposing research hypotheses. Section 3 details the research methodology, from questionnaire design to data collection and data analysis procedures. Section 4 presents the results of the data analysis. Detailed discussions of the analysis results and the conclusions are presented in Sections 5 and 6, respectively.

2. Literature review

Haber and Stornetta (1991) initially proposed the concept of BT, which is a peer-to-peer transaction network that verifies and stores data using a chain-like data structure formed by blocks, generates and updates data using distributed node consensus algorithms, and ensures the security of data transmission and access through cryptographic methods. Supported by this technology, information is transparent and open, addressing the security issues associated with trust-dependent centralized models and ensuring that data is immutable and tamper-proof (Swetha and JoePrathap, 2022). By recording information on the blockchain and using smart contracts, real-time tracking of material production, processing, circulation, and delivery can be achieved, effectively resolving the issues of information opacity, lack of trust, and poor communication in upstream and downstream supply chains (Perera et al., 2020). Through automated smart contracts, BT can reduce transaction costs and time, and prevent contract fraud (Goyal et al., 2023). Therefore, it is imperative to explore the factors influencing the BT adoption in ASCs to promote its application and advancement in agricultural development.

2.1. Security and privacy, management support, and policy support

Security and Privacy (SAP) are fundamental technical attributes of information technology, concerning the reliability of technical systems and the confidentiality of user data (Abdulsalam and Hedabou, 2021). While BT provides inherent data immutability, effectively managing it without compromising user privacy and ensuring information security remains a key factor in technology adoption. Policy Support (PLS) refers to the regulatory and policy environment provided by governments and related institutions. Clear regulations can reduce the legal risks for enterprises when adopting technology, while policy incentives such as subsidies and tax benefits can lower economic burdens and increase the interest of enterprises in adopting innovative technologies (Badghish and Soomro, 2024; Su et al., 2021).

Management Support (MGS) reflects an organization's internal resource allocation tendencies and the degree of support in management decisions, serving as a crucial driving force for the implementation of new technologies (AbuAkel and Ibrahim, 2023). Bialas et al. (2023) hold that top management support and cost-effectiveness are critical in business environments. Tsai et al. (2023) identified the lack of government regulation as the most significant barrier to blockchain adoption in ASC. Chittipaka et al. (2023) verified that BT adoption in emerging markets is simultaneously influenced by technical factors such as security, trust, and relative advantage, environmental factors such as regulatory support and rivalry pressure, organizational factors such as higher authority support and firms' IT resources.

In light of the aforementioned evidence, the following hypotheses are proposed:

H1 Security and privacy are negatively correlated with blockchain adoption intention.

H2 Management support is positively correlated with blockchain adoption intention.

H3 Policy support is positively correlated with blockchain adoption intention.

2.2. Perceived usefulness

Perceived Usefulness (PU) refers to the balance between the perceived benefits that users can derive from adopting new technology and the actual costs required for its adoption (Eisenhardt and Graebner, 2007). Davis (1989) introduced the TAM model, stating that PU can also serve as a mediator between external variables and technology adoption intention. Pugh (1966) highlighted the decision to adopt or not within an organization is also made by its members. Kabir (2021) found PU was a most important influencing factors in studying BT adoption behavior in Bangladesh. However, he also noted that inconsistencies in sample objects, sample sizes, and survey contexts often lead to inconsistent conclusions. The following hypotheses are proposed:

H4 Security and Privacy is positively correlated with perceived usefulness.

H5 Management support is positively correlated with perceived usefulness.

H6 Policy support is positively correlated with perceived usefulness.

H7 Perceived usefulness mediates the relationship between security and privacy and blockchain adoption intention.

H8 Perceived usefulness mediates the relationship between management support and blockchain adoption intention.

H9 Perceived usefulness mediates the relationship between policy support and blockchain adoption intention.

2.3. Perceived cost

Perceived Cost (PC) refers to all costs perceived by users before adopting an innovative technology or introducing a new device (Agarwal and Karahanna, 2000). Cost-benefit analysis holds that even if management perceives BT to have broad application prospects, the actual consideration of whether to adopt must align with the financial capacity to bear the associated costs (Layard and Glaister, 1994). Lee et al. (2001) found that when users perceive higher switching costs associated with adopting new technologies, the effect of PEOU and PU on adoption intention is greater. Yap et al. (2023) pointed out that cost is a significant perceived barrier to adopting blockchain traceability platforms in the Vietnamese fruit supply chain. Cao et al. (2024), in their study using a tripartite game model to examine the introduction of blockchain platforms in water-saving practices, found that costs have different impact effects on various stakeholders. Therefore, this study introduced PC as a moderating factor, proposed the following hypothesis:

H10 Perceived cost moderates the relationship between perceived usefulness and blockchain adoption intention.

In summary, the research model of this study was established as **Figure 1**:

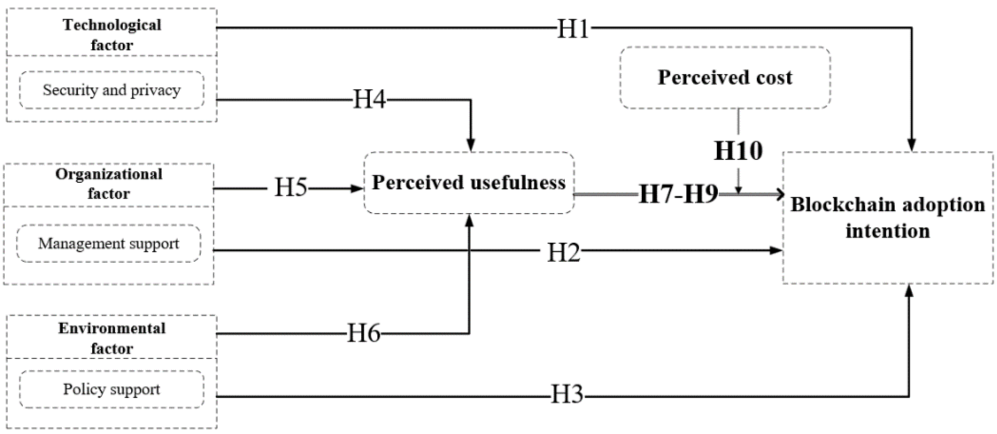

Figure 1. The research model for blockchain adoption intention in ASCs.

3. Research method

3.1. Survey measures

This study employs a quantitative research methodology for the empirical analysis. The questionnaire was initially designed based on the aforementioned research objectives, mainly referred to and adapted from the maturity measurement scales in previous literature. Subsequently, the cultural-adaptive modification and the one-to-one back-translation between English and Chinese were employed to render the questionnaire suitable for Chinese context (Brislin, 1970). Following the initial confirmation of the questionnaire's reliability and content validity through small-scale testing in a logical manner, the formal scale for this study was finalized. The detailed measurement items for each construct were listed in Appendix, comprising a total of 22 items.

3.2. Sampling process

Following the validation of the questionnaire, the sampling process will commence. The unit of analysis was determined as the single agricultural organization within Henan Province, which is the largest agricultural province in China. Given the nascent stage of BT application in ASCs and considering the practical feasibility of data acquisition, this study employed a combination of convenience sampling and snowball sampling methods (Biernacki and Waldorf, 1981). This approach aims to capture the unique perspectives and experiences of agricultural organizations in this region regarding BT adoption, thereby providing a rich empirical data foundation for the study.

Data collection was conducted through offline visits, either by distributing printed questionnaires or by forwarding Questionnaire Star links in person at locations preferred by participants. A total of 87 valid questionnaires were collected over a period of three weeks. According to the "10-times rule" (Kock and Hadaya, 2018), the sample size should be at least ten times the maximum path coefficient in a model. Therefore, the preliminary collection of these 87 questionnaires is in accordance with this guideline.

3.3. Data analysis

PLS-SEM is suitable for small sample analyses and does not require strict normal distribution assumptions for the sample, which is particularly applicable to complex models that involve both mediating and moderating variables (Chin, 2009; Chin and Newsted, 1999; Hair et al., 2012). Therefore, the collected data will be analyzed following the PLS-SEM analysis procedure outlined by Wong (2013), mainly divided into the measurement model assessment and structural model assessment. Based on those assessment standards in the two-stage approach by Hair et al. (2017), the assessment of measurement model primarily encompasses reliability analysis, convergent validity and discriminant validity analysis; The analysis of structural model mainly comprises covariance analysis, validity analysis and path relationship analysis.

The subsequent PLS-SEM analysis is conducted utilizing SmartPLS 4.0 software. This is a widely used software for theoretical verification of hypothesis models and for evaluating research hypotheses comprehensively (Ma and Agarwal, 2007). The measurement models of the three independent variables, the mediator variable, the moderator variable, and the dependent variable were initially constructed based on the relevant theories and measurement questions. Subsequently, the structural model of this study was established based on the previously proposed hypothesized path relationships. The PLS-SEM model output including both measurement model and structural model is shown in **Figure 2**. The subsequent model analysis would be mainly based on the PLS-algorithm, bootstrapping, blindfolding, and IPMA analysis functions of the SmartPLS 4.0.

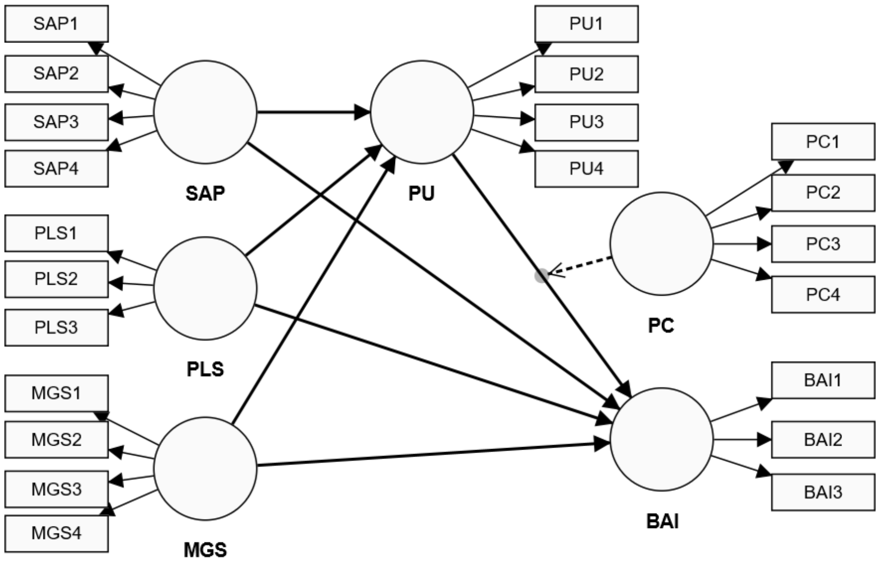

Figure 2. PLS-SEM model.

4. Empirical results

4.1. Descriptive statistical analysis

Descriptive statistical analysis was conducted using SPSS 26.0. Among the 87 valid samples, 25 are medium-to-large enterprises, while the remaining 62 are small and micro-enterprises. The participating middle and senior managers were evenly distributed between male and female. 48 participants held the position of production department, and 28 are from the operational department. In terms of educational background, 38% of participants had a master's degree or higher, while 62% held a bachelor's degree or lower. Regarding work experience, 35 participants have been working for 11–15 years, 41 participants have already been over 16 years.

The detailed results of the statistical indicators are presented in **Table 1**. The mean values for each item are approximately 3, while the variance for each item is around 2, suggesting a moderate degree of dispersion in the sample data. The absolute values of the skewness and kurtosis coefficients are less than 2, indicating that there are no significant biases or fluctuations in the overall sample's evaluation.

Table 1. Statistical indicators for each item.

Construct	Items	Mean	Standard deviation	Skewness	Kurtosis
Security and privacy (SAP)	SAP 1	2.770	1.387	−0.024	−1.431
	SAP 2	2.897	1.175	0.031	−0.990
	SAP 3	2.943	1.488	−0.070	−1.517
	SAP 4	3.046	1.183	0.037	−0.948
Management support (MGS)	MGS 1	3.264	1.410	0.118	−1.614
	MGS 2	3.195	1.477	−0.214	−1.376
	MGS 3	3.172	1.440	−0.097	−1.374
	MGS 4	3.230	1.483	−0.169	−1.481

Table 1. (*Continued*).

Construct	Items	Mean	Standard deviation	Skewness	Kurtosis
Policy support (PLS)	PLS 1	3.023	1.381	−0.042	−1.345
	PLS 2	2.920	1.464	−0.059	−1.466
	PLS 3	3.115	1.458	−0.068	−1.392
Perceived usefulness (PU)	PU 1	3.023	1.134	0.050	−0.348
	PU 2	3.034	1.088	0.040	−0.132
	PU 3	3.034	1.066	−0.070	−0.135
	PU 4	3.080	1.177	0.014	−0.541
Perceived cost (PC)	PC 1	2.908	1.301	−0.273	−1.264
	PC 2	3.080	1.416	0.053	−1.374
	PC 3	3.345	1.163	−0.396	−0.654
	PC 4	3.218	1.401	−0.297	−1.304
Blockchain adoption intention (BAI)	BAI 1	2.828	1.416	0.213	−1.175
	BAI 2	2.759	1.633	0.285	−1.575
	BAI 3	2.747	1.424	0.240	−1.277

4.2. Measurement model

In order to validate the reliability of the measurement model, convergent validity and discriminant validity were assessed (Hair et al., 2012). **Table 2** reports the alpha values, composite reliability (CR), factor loadings, and average variance extracted (AVE) values obtained through PLS-algorithm analysis. All alpha values exceed 0.8, CR values exceed 0.7, factor loadings exceed 0.7, and AVE values exceed 0.5, indicating the model exhibits good reliability and high internal consistency, thereby meeting the standards for convergent validity analysis (Cronbach, 1951; Chin, 1998; Fornell and Larcker, 1981; Nunnally and Bernstein, 1994; Werts et al., 1974).

Table 2. Reliability and convergent validity analysis.

Construct	Items	Cronbach's α	Factor loading	CR	AVE
SAP	4	0.890	0.847–0.892	0.934	0.746
MGS	4	0.931	0.903–0.928	0.935	0.829
PLS	3	0.874	0.871–0.917	0.887	0.797
PU	4	0.866	0.804–0.886	0.867	0.714
PC	4	0.891	0.851–0.881	0.932	0.750
BAI	3	0.904	0.903–0.925	0.907	0.839

Tables 3–5 report the discriminant validity indices defined according to three standards: Fornell and Larcker criterion, cross-loadings, and Heterotrait-monotrait ratio (HTMT) (Chin, 1998; Fornell and Larcker, 1981; Henseler et al., 2015). In **Table 3**, the Fornell and Larcker criterion shows that the AVE of each construct is greater than the squared correlation of the construct (the diagonal value in bold should be greater than the inter-construct correlation values). In **Table 4**, each construct's cross-loading is smaller than its factor loading (the value in bold should

be greater than others). In **Table 5**, all HTMT values are less than 0.85. All three standards meet the evaluation requirements, indicating the model has demonstrated discriminant validity.

Table 3. Fornell and Lacker criterion analysis.

Construct	BAI	MGS	PC	PLS	PU	SAP
BAI	**0.916**					
MGS	0.325	**0.91**				
PC	0.377	0.041	**0.866**			
PLS	0.501	0.147	0.262	**0.893**		
PU	0.554	0.350	0.232	0.337	**0.845**	
SAP	0.241	−0.113	0.286	−0.037	0.023	**0.863**

Table 4. Cross-loadings analysis.

Item	BAI	MGS	PC	PLS	PU	SAP
BAI1	**0.903**	0.251	0.280	0.438	0.470	0.264
BAI2	**0.925**	0.324	0.387	0.520	0.522	0.190
BAI3	**0.920**	0.313	0.361	0.414	0.528	0.212
MGS1	0.273	**0.928**	0.031	0.084	0.277	−0.110
MGS2	0.318	**0.903**	0.034	0.116	0.357	−0.111
MGS3	0.314	**0.905**	−0.020	0.170	0.308	−0.077
MGS4	0.271	**0.905**	0.104	0.160	0.324	−0.114
PC1	0.269	0.028	**0.851**	0.178	0.188	0.225
PC2	0.308	0.040	**0.878**	0.128	0.133	0.282
PC3	0.422	0.033	**0.881**	0.344	0.291	0.263
PC4	0.253	0.041	**0.853**	0.207	0.149	0.206
PLS1	0.444	0.135	0.283	**0.917**	0.304	−0.029
PLS2	0.384	0.084	0.215	**0.871**	0.250	−0.065
PLS3	0.500	0.163	0.205	**0.890**	0.338	−0.011
PU1	0.434	0.294	0.235	0.259	**0.830**	0.062
PU2	0.421	0.358	0.180	0.281	**0.886**	−0.021
PU3	0.524	0.191	0.092	0.303	**0.859**	0.054
PU4	0.487	0.340	0.274	0.292	**0.804**	−0.014
SAP1	0.117	−0.184	0.207	−0.004	0.010	**0.848**
SAP2	0.211	−0.075	0.157	−0.058	0.043	**0.847**
SAP3	0.176	−0.110	0.202	0.026	0.025	**0.892**
SAP4	0.267	−0.070	0.367	−0.061	0.002	**0.866**

Table 5. HTMT analysis results.

Construct	BAI	MGS	PC	PLS	PU	SAP
BAI						
MGS	0.350					
PC	0.399	0.060				

Table 5. (*Continued*).

Construct	BAI	MGS	PC	PLS	PU	SAP
PLS	0.555	0.157	0.280			
PU	0.623	0.387	0.249	0.382		
SAP	0.250	0.139	0.297	0.059	0.071	

4.3. Structural model

Prior to evaluating the structural model, it is essential to check for collinearity among the exogenous variables using the variance inflation factor (VIF). Generally, a VIF value less than 3.3 indicates the absence of collinearity (Kock and Lynn, 2012). Subsequently, the bootstrapping function is employed to conduct 5000 resamples, thereby facilitating the acquisition of the structural model's coefficient of determination (R^2) and effect size (f^2). The coefficient of R^2 indicates the proportion of variance explained by the model, with the value greater than 0.33 generally considered to indicate moderate explanatory power (Chin, 1998). Additionally, the benchmark for R^2 can vary depending on the specific research context; in social science research, an R^2 value of at least 0.1 is considered acceptable (Ozili, 2023). Thus, this model has sufficient explanatory power. The PLS-SEM analysis after running Bootstrapping was depicted in **Figure 3**.

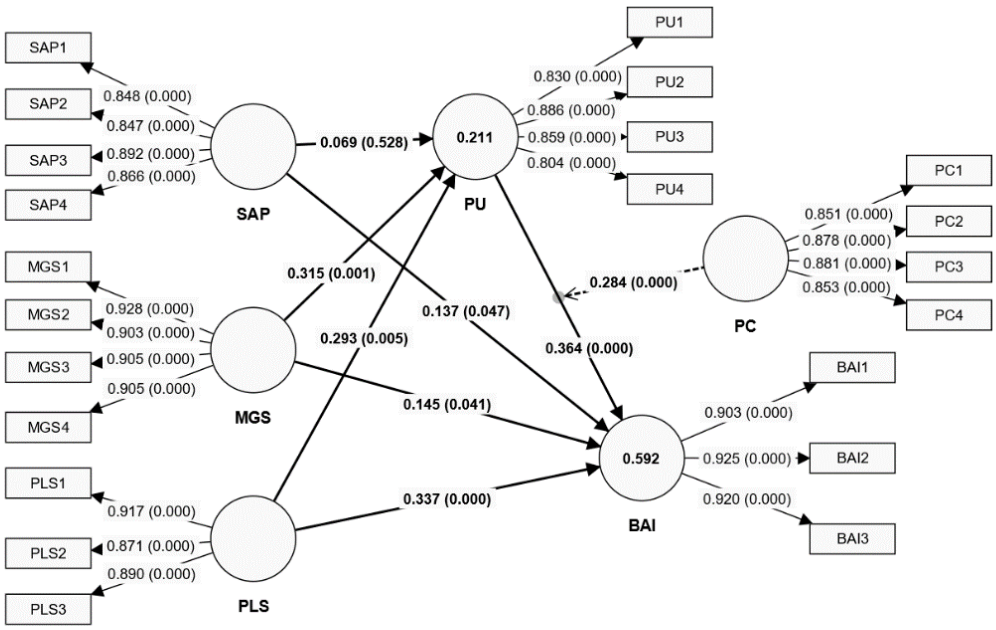

Figure 3. The PLS-SEM model after bootstrapping.

Except for the inadequate explanatory power of SAP on PU (f^2 < 0.02), the remaining indicators demonstrate a range of impact levels. Ultimately, the Blindfolding function is used to obtain the predictive relevance (Q^2) value, where a higher Q^2 value indicates stronger predictive relevance. The Q^2 value greater than 0 indicates that the prediction error of PLS-SEM is less than the error predicted by the mean (Stone, 1974). **Table 6** presents the detailed values of the structural validity indices mentioned above.

Table 6. Structural validity analysis results.

Path	VIF	R^2	f^2	Q^2
MGS ⟶ BAI	1.173	0.592	0.044	0.472
PC ⟶ BAI	1.222		0.054	
PLS ⟶ BAI	1.192		0.234	
PU ⟶ BAI	1.303		0.250	
SAP ⟶ BAI	1.227		0.038	
MGS ⟶ PU	1.034	0.211	0.122	0.133
PLS ⟶ PU	1.034		0.107	
SAP ⟶ PU	1.013		0.006	

Significance results from path coefficient analysis can be used to assess the validity of the path relationships. In a two-tailed test, *T*-values greater than 1.96 and P-values less than 0.05 typically indicate statistical significance at a 95% confidence level (Hair, 2009). **Table 7** illustrates that, with the exception of H4 and H7, all the path relationships are statistically significant. It's noteworthy that although the relationship between SAP and BAI (H1) meets the statistical standards, the beta value is in opposition to the initial hypothesis, indicating a discrepancy between the observed and expected results.

Table 7. Path coefficients results.

Path relationships	Original sample	Standard deviation	T values	*P* values	2.5%	97.5%	Results
H1: SAP ⟶ BAI (−)	0.137	0.069	1.991	0.047	0.000	0.271	Not Supported
H2: MGS ⟶ BAI (+)	0.145	0.071	2.041	0.041	0.009	0.282	Supported
H3: PLS ⟶ BAI (+)	0.337	0.071	4.745	0.000	0.199	0.481	Supported
H4: SAP ⟶ PU (−)	0.069	0.110	0.632	0.528	−0.137	0.285	Not Supported
H5: MGS ⟶ PU (+)	0.315	0.094	3.364	0.001	0.131	0.492	Supported
H6: PLS ⟶ PU (+)	0.293	0.105	2.800	0.005	0.095	0.499	Supported
H7: SAP ⟶ PU ⟶ BAI	0.025	0.041	0.613	0.540	−0.049	0.114	Not Supported
H8: MGS ⟶ PU ⟶ BAI	0.115	0.042	2.710	0.007	0.039	0.205	Supported
H9: PLS ⟶ PU ⟶ BAI	0.107	0.039	2.776	0.006	0.035	0.186	Supported
H10: PC × PU ⟶ BAI	0.284	0.070	4.084	0.000	0.145	0.418	Supported

Theoretically, the analysis of moderating effects involves first analyzing the model without the moderating variable and then analyzing the model with the moderating variable to estimate the moderating effect by comparison (Becker et al., 2023). First, the PLS-algorithm function is used to obtain the correlation coefficients of the moderating paths, and then the significance of the moderating effect is determined using the bootstrapping function. The results in **Table 7** for the moderating effect (H10) are statistically significant, indicating that PC moderates the relationship between PU and BAI. **Figure 4** illustrates the interaction effects among them more clearly.

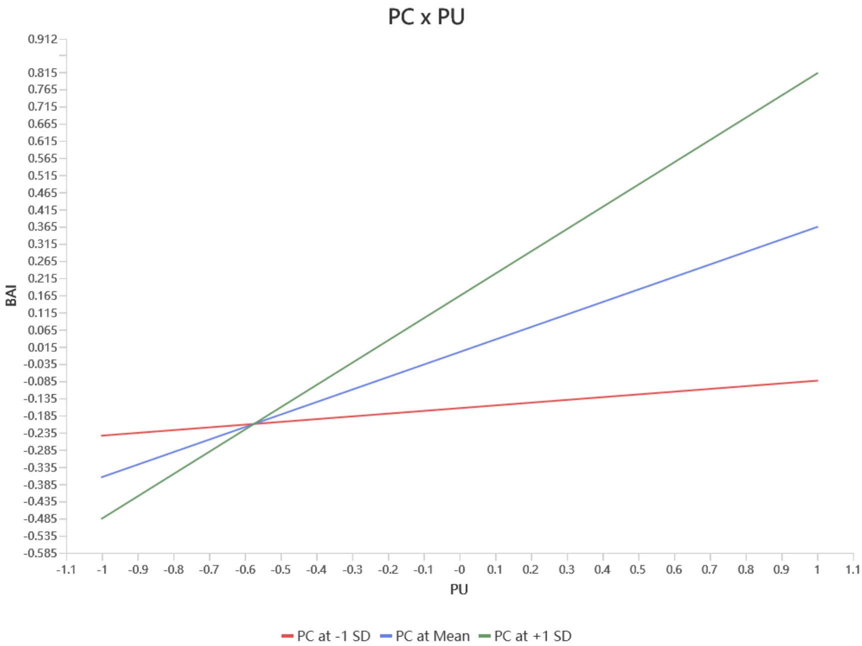

Figure 4. Simple slope analysis for moderating effects.

4.4. IPMA analysis

Importance-Performance Matrix Analysis (IPMA) is depicted in **Figure 5**, which vividly illustrates the impact of exogenous variables on endogenous variables. This analysis is crucial for prioritizing areas needing improvement, enhancing the PLS-SEM results (Henseler et al., 2015). The matrix, centered at (0.3, 0.5), is divided into four quadrants. Quadrant I indicates high-importance, high-performance constructs that are both important and effective. Quadrant II includes low-importance, high-performance constructs that overperform relative to their strategic importance. Quadrant III encompasses low-importance, low-performance constructs that are neither important nor effective, thus having low priority. Quadrant IV identifies high-importance, low-performance constructs that are crucial but underperforming, requiring immediate attention to improve their performance. In this study, the five constructs show similar performance, which is generally suboptimal. PLS has the highest importance but only performs moderately, near the median. MGS performs best but has low importance, indicating over-performance.

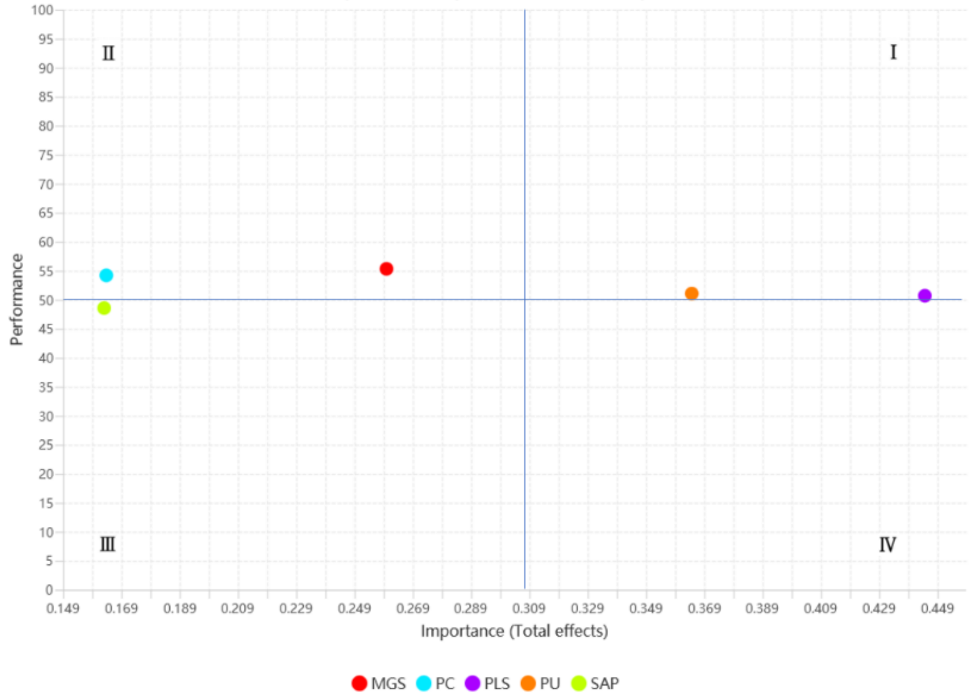

Figure 5. Importance-performance map.

5. Discussion

The findings of this study emphasized the managerial implications for academics and practitioners. Based on the results of H1, H2 and H3, the direct effects of organizational and environmental factors on BT adoption in ASCs were approved, and the organizational factor exhibited stronger effects. This finding aligned with Bawono et al. (2022), which reported that organizational factors are the most important influencing technology adoption intention. Moreover, Chittipaka et al. (2023) and Tsai et al. (2023) also confirmed that the external incentives and internal management significantly influence technology adoption intentions. The critical mediating role of PU was highlighted by the supported hypotheses corresponding with the fourth research question of this study, which illustrates that the technology acceptance model applicable to this study, where management's perceived usefulness of emerging technologies promotes technology adoption (Davis, 1989). This result was also confirmed in the agricultural supply chain by Saha et al. (2024), which held that the perceived usefulness of decision-makers can enhance their likelihood of adopting blockchain technology.

Surprisingly, while the direct relationship between SAP and BAI (H1) was statistically significant, it was not supported Because of the opposite role manifestation. The 95% confidence interval included zero value and PU's mediating role between them (H7) was not supported, indicating the limited effects and marginal significance of this technological factor. This contradicts with the Deloitte (2021), which clearly identified security and privacy of data as the most important dimension for enhancing the BT adoption. This finding was also inconsistent with Mishra et al. (2024), which found technical factors to be fundamental for adopting innovative technology, with a greater impact on BT adoption than organizational and environmental factors. A possible reason is that emphasizing SAP alone is insufficient to enhance users' perceptions; combining these factors with others to provide tangible organizational value is necessary (Chittipaka et al., 2023).

The IPMA analysis provided a clearer guidance on practical applications. Results indicate that while each construct's performance is similar, the overall performance is suboptimal, hovering around the median. Despite PLS's highest importance, its performance is only median, suggesting its practical impact has not reached optimal potential and requires enhancement. This may be due to ineffective implementation, insufficient incentives, or gaps between policy formulation and practice. Although MGS has the maximum effect, it stayed in the second quadrant with PC under the lower importance, implying relatively overemphasis on these constructs relative to their strategic value. This may be related to the sample data, with a high proportion (71%) of small and micro enterprises whose weak organizational mechanisms and financial foundations hinder technology adoption (Rupeika-Apoga and Petrovska, 2022), likely causing bias in the analysis.

The contribution of this study to theoretical applications should not be overlooked. By integrating the TAM model and the TOE framework within the context of ASCs, this study addresses the gaps identified by Wang et al. (2022), who highlighted the relative scarcity of research on blockchain technology in the agricultural sector. Furthermore, it provides a more comprehensive theoretical perspective for exploring the antecedents of blockchain technology adoption. Through introducing perceived cost as a moderating variable, it embeds cost-benefit theory into the research framework, further extending the theoretical model and offering new insights for future studies. At the same time, highlighting the mediating role of perceived usefulness fosters the development of interdisciplinary research across the fields of technology, management, and agriculture.

6. Conclusion

In summary, this study provides a new perspective on innovative technology adoption and empirical support for the blockchain adoption in ASCs. The conclusions indicate that strengthening policy implementation is crucial for advancing technology adoption. Monitoring and evaluating policy effectiveness, adjusting measures, and refining the framework ensure genuine promotion of emerging technologies. Enhancing management and employee awareness of BT's potential value, and improving recognition among agricultural enterprises, are also effective strategies. Core technical factors like SAP need further exploration. Disseminating knowledge about SAP protection, increasing awareness of blockchain's advantages, and enhancing understanding of its attributes and effectiveness are essential. These efforts will promote the widespread and effective adoption of BT in ASCs.

Given the limited research resources and data availability, this study focuses on agricultural companies in Henan Province of China. The analysis results might be influenced by regional policy constraints. Future research should be conducted in different social systems to validate the universality of policy effectiveness across various cultural backgrounds. The impact of SAP needs further analysis, suggesting an increased sample size, long-term data tracking, or more control variables to improve estimate accuracy and stability. Future research could also refine application scenarios by comparing BT adoption in different types of ASCs, such as vegetables, fish, or other products, to better understand the drivers of blockchain adoption.

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Appendix

Appendix Measurement items of constructs.

Construct	Measurement item	Source
Security and Privacy (SAP)	SAP 1. There might existed personal privacy risks. SAP 2. There might existed information leakage risks. SAP 3. There might existed access control risks. SAP 4. There might existed legality risks.	Maroufkhani et al. (2020); Salleh and Janczewsk (2016)
Management Support (MGS)	MGS 1. The senior managers actively embrace innovation. MGS 2. The senior managers are willing to allocate resources for the technology adoption. MGS 3. The senior managers are ready to accept the risks associated with the technology adoption. MGS 4. The senior managers encourage employees to actively apply blockchain in daily work.	Wong et al. (2020)
Policy Support (PLS)	PLS 1. Government policy supports the technology adoption. PLS 2. Government provides incentives to the technology adoption. PLS 3. Government has already provided enough facilities to promote the technology adoption.	Malik et al. (2021)
Perceived Usefulness (PU)	PU 1. The technology can enhance the operational effectiveness. PU 2. The technology can increase the productivity. PU 3. The technology can improve corporate performance. PU 4. The innovative technology is useful in daily job.	Venkatesh and Davis (2000)
Perceived Cost (PC)	PC 1. The setup costs are high. PC 2. The running costs are high. PC 3. The training costs are high. PC 4. The lead time is long.	Lin (2014)
Blockchain Adoption Intention (BAI)	BAI 1. Our company intends to adopt the technology actively. BAI 2. Our company has already developed an application plan to adopt it. BAI 3. Our company intends to actively recommend it to others.	Kim et al. (2016)