

Date	Submitted	Accepted	Published
	5 th December 2025	17 th April 2026	6 th June 2026

DETERMINANTS OF DIGITAL TRANSFORMATION ADOPTION IN THE GOVERNANCE OF AGRICULTURAL COOPERATIVES: EVIDENCE FROM VIETNAM

Huong NTT^{1*} and NTT Phuong²



Huong Nguyen Thi Thu

*Corresponding author email: thuhuong.nt@tmu.edu.vn

ORCID: <https://orcid.org/0009-0008-8739-1759> - NTT Huong

ORCID: <https://orcid.org/0000-0001-8662-3580> - NTT Phuong

¹Institute of Accounting and Auditing, Thuongmai University, Hanoi, Vietnam

²Institute of Accounting and Auditing, Thuongmai University, Hanoi, Vietnam



ABSTRACT

Digital transformation in agricultural cooperatives remains critically underdeveloped in emerging economies, yet the determinants of its adoption are poorly understood within the cooperative governance context. This study investigated the multidimensional factors shaping digital transformation adoption among fruit-growing cooperatives in Son La province, Vietnam, one of the country's most strategically significant agricultural regions. As digital transformation becomes increasingly essential for enhancing productivity, transparency, and competitiveness in the agricultural sector, understanding the drivers and barriers specific to cooperative organizations operating in mountainous and resource-constrained regions remains both timely and necessary. Using an integrated Technology-Organization-Environment (TOE) framework extended with the Diffusion of Innovations (DOI) model and a managerial capability dimension, this study employs a rigorous mixed-method approach that combines quantitative survey analysis with qualitative insights gathered from in-depth discussions with cooperative leaders. Survey data were collected from 300 managers and members across 50 representative cooperatives and subsequently analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS. The model demonstrates strong explanatory power ($R^2 = 0.748$), and all 11 hypotheses were supported. Among the factors examined, managerial factors, most notably managerial digital competence ($\beta = 0.361$, $p = 0.001$) and competitive pressure ($\beta = 0.309$, $p = 0.004$), emerged as the strongest positive drivers, functioning as key catalysts that exert a strong and consistent influence on cooperative readiness and willingness to embrace digital technologies. In contrast, organizational capacity, particularly human resource capacity deficits ($\beta = -0.503$, $p < 0.001$), constituted the most significant barrier, creating a structural bottleneck that hampers digital initiatives, delays implementation, and reduces the overall effectiveness of transformation efforts. This study extends the TOE framework by formally incorporating managerial capability as a fourth contextual dimension, offering both theoretical advancement and practical guidance for policymakers and cooperative managers seeking to accelerate digital agriculture in mountainous, resource-constrained settings across emerging economies.

Key words: Determinants, Digital transformation, TOE, DOI, PLS-SEM, cooperatives, agricultural sector, Vietnam

Citation: **Huong NTT and NTT Phuong** Determinants of Digital Transformation Adoption in the Governance of Agricultural Cooperatives: Evidence from Vietnam. *Afr. J. Food Agric. Nutr. Dev.* 2026; **26(4)**: 29336-29341. <https://doi.org/10.18697/ajfand.151.26690>



INTRODUCTION

The agricultural sector is currently facing unprecedented pressure to ensure food security for the world's population, driven by increasingly scarce resources and the negative impacts of climate change [1]. To address this challenge, digital transformation has emerged as a crucial trend and strategic pillar for the industry's sustainable development [2]. The deep integration of disruptive technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and Big Data is transforming the agricultural landscape. This shift is moving away from experience-based models towards precision farming and data-driven governance [3].

Vietnam's agricultural sector is undergoing a significant transformation to achieve sustainable development and enhance its competitiveness in international markets. In this context, digital technology is recognized as a breakthrough solution to optimize production processes, management, and market access. Given its importance, the Vietnamese government has identified agriculture as one of the eight priority sectors in the "National Digital Transformation Program for 2025, with a vision for 2030" [4].

Son La province is currently one of the leading fruit production hubs in Vietnam. Between 2016 and 2025, the province has implemented a program to convert and newly plant nearly 62,000 hectares of fruit, bringing the total area of fruit-growing, including the Son Tra tree, to 85,000 hectares. With a projected output of 510,000 tons by 2025, Son La has established itself as the region with the largest fruit-growing area in Northern Vietnam and the second largest nationwide [5]. In the context of modern agricultural development, Son La faces an urgent need for digital transformation to optimize production processes and establish sustainable value chains. Agricultural cooperatives play a vital role in organizing production and connecting farmers to the market. However, practical evidence indicates that the digital transformation process within agricultural cooperatives across the country, and specifically in Son La, is progressing slowly and encountering numerous challenges. According to data from the Ministry of Agriculture and Rural Development in 2024, approximately 30% of agricultural enterprises in Vietnam have adopted one or more digital technologies for production. This figure is significantly lower than the 50% target set for 2025. Furthermore, a report titled "Assessment of the Current State and Trends of Digital Transformation in Vietnam's Agriculture" from the Institute of Policy and Strategy for Agriculture and Rural Development in 2023 reveals that only 15% of cooperatives and farms utilize digital production management systems, while the majority still depend on traditional methods. In Son La, cooperatives are beginning to adopt software and digital transformation solutions for managing the One Commune One Product (OCOP) Program; however, this

process is still in its early stages and progressing slowly. By 2024, 42 enterprises and cooperatives had received support to promote their products on digital platforms, but this number remains modest compared to the total number of agricultural cooperatives in the province [6]. Despite this urgency, existing research leaves three important gaps unaddressed. First, a context gap persists. Agricultural cooperatives are not ordinary Small and Medium-sized Enterprises (SMEs). Their dual economic-social mandate, collective governance structure, and member heterogeneity create adoption dynamics that standard TOE studies conducted in corporate settings fail to capture. Second, a theoretical gap exists in that the canonical TOE framework lacks an explicit managerial dimension, yet the cooperative literature consistently identifies leadership quality as a pivotal enabler of organizational change. Third, a methodological gap remains that very few quantitative TOE studies have been conducted in mountainous, upland agricultural regions of Southeast Asia, leaving it unclear whether findings from lowland or urban contexts transfer to resource-scarce, geographically isolated cooperatives. This study addresses all three gaps by extending the TOE framework with a formal managerial capability dimension, applying an integrated TOE-DOI-managerial model to fruit-growing cooperatives in Son La province, and providing the large-sample Partial Least Squares Structural Equation Modeling (PLS-SEM) evidence on the determinants of digital transformation in this understudied context. The findings are expected to advance the theoretical framework of technology adoption in agricultural cooperative governance while offering actionable guidance for cooperative managers and policymakers.

LITERATURE REVIEW AND THE RESEARCH MODEL

Digital Transformation: From concept to the governance context of agricultural cooperatives

Digital Transformation has evolved from a technology-focused concept to a comprehensive model for organizational change. It involves a continuous, strategic process where organizations harness digital technologies to reshape business models, operational processes, and work culture, aiming for a sustainable competitive advantage [7]. Recent research emphasizes that digital transformation is an ongoing capability, enabling organizations to adapt and thrive in an increasingly uncertain and digitized environment [8,9].

In agriculture, digital transformation, also known as Agriculture 4.0, is driving a significant change in production and management methods. It integrates key technologies such as the Internet of Things (IoT), which collects real-time data from sensors, Big Data Analytics, which transforms raw data into actionable insights for decision-making, Artificial Intelligence (AI), which develops predictive and



optimization models and Blockchain, which enhances transparency and traceability [10]. Recent research not only examines the technical aspects of Agriculture 4.0 but also explores its socio-economic impacts, including the restructuring of value chains and the new skill requirements for the agricultural workforce [1].

However, the implementation of digital transformation in agricultural cooperatives presents a unique set of challenges and opportunities. As dual-purpose organizations that aim for both economic efficiency and social missions [11], cooperatives often face limitations such as small scale, restricted financial resources, and varying skill levels among their members. This creates a "digital divide," not only between cooperatives and large corporations but also within the collective economic sector itself [12]. Consequently, a clear understanding of the factors influencing the adoption and success of digital transformation in this context is essential, necessitating a multi-dimensional and comprehensive analytical framework.

Theoretical foundation and proposed research model

To identify the complex drivers and barriers of digital transformation in cooperatives, this study developed an integrated model based on two well-established theories: the Technology-Organization-Environment (TOE) framework and the Diffusion of Innovations (DOI) theory.

The TOE Framework: The Technology-Organization-Environment (TOE) framework is a comprehensive model that explains the contextual factors influencing technology adoption within organizations [13]. According to this framework, the adoption of technological innovations is affected by three main groups of factors: the technological context, the organizational context, and the environmental context. Each of these groups includes factors that can either promote or hinder the adoption process. The TOE model has been validated and extended through numerous studies across various fields, including digital transformation, artificial intelligence, and information system innovation. Its strength lies in its ability to fully reflect the internal and external factors that impact technology adoption behavior [14]. In the context of agricultural cooperatives, which often face resource constraints and multiple institutional pressures, the TOE framework serves as a suitable theoretical tool to explain how technological capabilities, organizational readiness, and the external environment work together to influence the implementation of digital transformation.

Diffusion of Innovations (DOI): While the TOE model provides strong explanatory power, it has been criticized for not fully addressing the perceptual and behavioral factors that influence decisions about technology adoption. To overcome this

limitation, this study integrates the Diffusion of Innovations (DOI) theory as a complementary framework. According to DOI theory, the adoption of an innovation depends on an individual's or organization's perception of five key characteristics: relative advantage, compatibility, complexity, trialability, and observability [16]. Incorporating DOI into the TOE framework allows for a more effective alignment between perceptions of technology (from DOI) and contextual conditions (from TOE). This integration provides a deeper understanding of how managers' perceptions and evaluations interact with internal capabilities and external factors to drive digital transformation. As a result, the combined TOE-DOI framework is now regarded as a robust theoretical foundation for explaining the adoption of digital transformation in small and medium-sized enterprises, as well as cooperative organizations [17,18]. This study extends the TOE framework by introducing managerial capability as a formal fourth dimension alongside the original technological, organizational, and environmental contexts. Whereas prior TOE studies treat such characteristics as implicit moderators or subsume them within organizational factors, leadership agency in small cooperative organizations is structurally distinct and should be modeled as an independent driver. This extension responds to calls in the cooperative governance literature for models that explicitly account for the central role of leaders in resource-constrained, collectively governed entities. The resulting four-dimensional TOE-DOI-Managerial model represents a theoretical contribution beyond the mere application of existing frameworks, offering a more complete and contextually grounded explanation of digital transformation adoption in agricultural cooperatives.

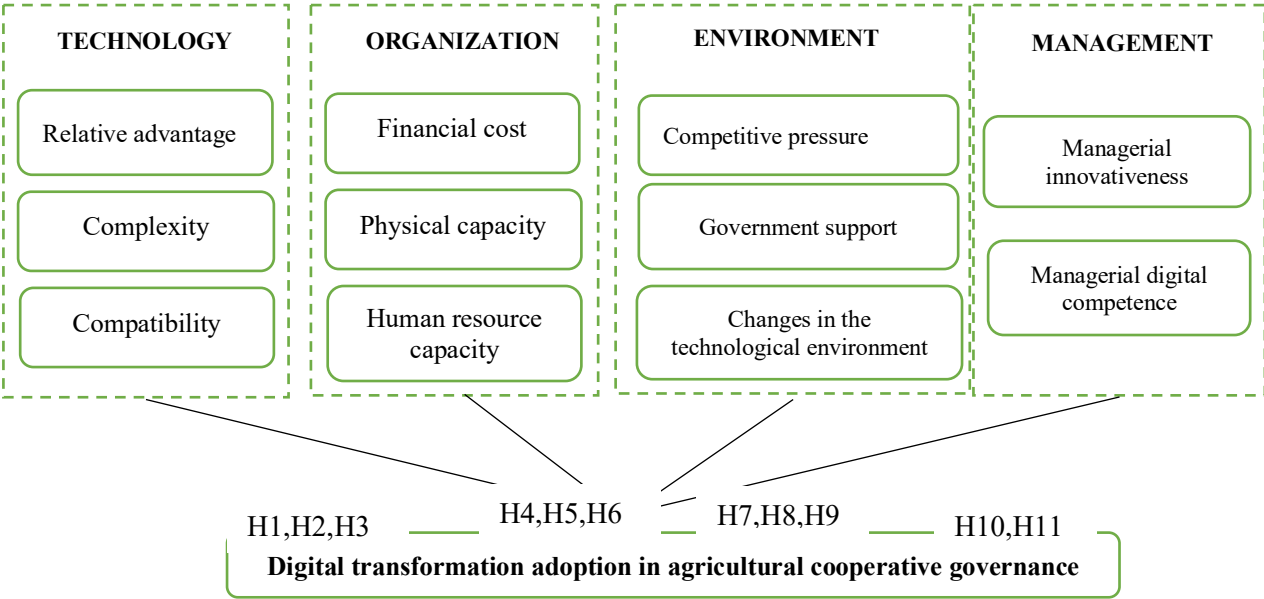


Figure 1: Research Model

Technological factors and their relationship with the adoption of digital transformation

Relative advantage refers to the extent to which a digital technology is perceived to enhance effectiveness or efficiency compared to traditional methods [16]. When a cooperative believes that digital transformation can increase productivity, lower costs, optimize management, and expand markets, its likelihood of adopting the technology increases.

Hypothesis H1: Greater relative advantage of digital technologies is positively associated with higher levels of digital transformation adoption in agricultural cooperative governance.

Complexity refers to the level of difficulty in understanding, using, and integrating a technology into existing governance processes. Complexity is a significant barrier to technology adoption in resource-constrained organizations [19]. For agricultural cooperatives, the lack of specialized human resources and experience in technology management can make the perceived complexity of digital transformation a reason for hesitation or delays in adoption.

Hypothesis H2: Greater perceived complexity of digital technologies is negatively associated with the level of digital transformation adoption in agricultural cooperative governance.

Compatibility is the extent to which digital transformation aligns with the existing processes, values, needs, and resources of the cooperative. The more compatible a technology is, the greater its rate of adoption. In the agricultural context, digital transformation solutions must be flexible enough to adapt to specific farming conditions, crop seasons, and the skill levels of farmers. If digital transformation can be easily integrated into cultivation processes, record-keeping, financial reporting, and current member management, its likelihood of adoption will increase [20].

Hypothesis H3: Greater compatibility between digital technologies and existing cooperative processes is positively associated with the level of digital transformation adoption in agricultural cooperative governance.

Organizational factors and their relationship with digital transformation adoption

Financial cost includes initial investments in software, hardware, personnel training, and ongoing operational maintenance. Cost is a common barrier for small and medium-sized organizations [21]. For cooperatives, particularly, limited financial resources can lead to hesitance in making investments that do not promise immediate returns. A report by the Food and Agriculture Organization (FAO) [2]

emphasizes that a lack of investment capital is the primary reason why agricultural organizations in Asia, including Vietnam, have struggled to fully achieve digital transformation.

Hypothesis H4: Higher financial costs of digital transformation are negatively associated with the level of digital transformation adoption in agricultural cooperative governance.

Physical capacity encompasses telecommunications infrastructure, technological equipment, and Internet accessibility. According to the Organisation for Economic Co-operation and Development (OECD) [22], one of the main obstacles to digital transformation adoption in rural areas is the absence of synchronized digital infrastructure. In Son La, many cooperatives still do not have the necessary software management systems or equipment to implement solutions such as blockchain, IoT, or basic Enterprise Resource Planning systems. Thus, physical capacity is a crucial prerequisite for digital transformation adoption. However, in resource-constrained and externally dependent contexts such as mountainous cooperatives, physical infrastructure is often provided by government agencies or mobile operators rather than developed internally by cooperatives. As a result, the mere presence of physical assets does not necessarily translate into organizational readiness or motivation to adopt digital tools. Cooperatives that perceive their existing infrastructure as adequate may paradoxically exhibit lower adoption urgency than those confronting visible infrastructure gaps. This context - specific logic suggests that in settings where infrastructure is externally supplied and organizational agency is limited, the relationship between physical capacity and digital transformation adoption may be negative rather than positive.

Hypothesis H5: In contexts where physical infrastructure is largely externally provided, higher perceived physical capacity is negatively associated with the level of digital transformation adoption in agricultural cooperative governance.

Human resource capacity, particularly regarding employees with technological knowledge, is a critical factor in the reception, operation, and maintenance of digital systems. A shortage of specialized personnel is one of the greatest barriers to digital transformation in agriculture [23]. Cooperatives often lack dedicated information technology departments, and management processes may still be conducted manually, making this deficiency a significant factor that influences digital transformation.

Hypothesis H6: Lower human resource digital capacity is negatively associated with the level of digital transformation adoption in agricultural cooperative governance.

Environmental factors and their relationship with digital transformation adoption

Competitive pressure from industry rivals or the quality standards required by export markets often drives organizational innovation. Competitive pressure is a significant catalyst for IT adoption in small and medium-sized enterprises (SMEs) [24]. For agricultural cooperatives, competition from private enterprises, foreign organizations, or the demands of retail chains (such as BigC and Vinmart) may compel them to undergo digital transformation to survive and thrive.

Hypothesis H7: Greater competitive pressure from the market is positively associated with the level of digital transformation adoption in agricultural cooperative governance.

Government support serves as a catalyst, helping cooperatives overcome financial, knowledge, and technological barriers. Policy, financial, and technical assistance from the state strongly influences the technology adoption behavior of small enterprises [25]. In Vietnam, numerous programs such as One Commune One Product (OCOP), the National Target Program for New Rural Development, and digital transformation support packages initiated by the Ministry of Agriculture and Rural Development are helping cooperatives in their digitalization efforts.

Hypothesis H8: Greater government support for digitalization is positively associated with the level of digital transformation adoption in agricultural cooperative governance.

Changes in the technological environment—such as the growth of e-commerce, traceability, and smart agriculture—have transformed the way operations are organized. A level of "compulsion" to digitize, stemming from the overall digitalization of the ecosystem, which forces enterprises and cooperatives to adapt or risk being left behind [26]. In the agricultural sector, innovations such as digital agricultural exchanges, QR code traceability, and the use of AI for irrigation and crop forecasting have made digital transformation a necessity.

Hypothesis H9: A more dynamic technological environment is positively associated with the level of digital transformation adoption in agricultural cooperative governance.

Managerial factors and their relationship with digital transformation adoption

Managerial innovativeness to experiment are crucial driving forces for digital transformation in small organizations. The CEO serves as the strategic director who directly influences innovation decisions within small enterprises [27]. Additionally, an

open mindset and a readiness to accept technological risks from leadership foster a "culture of innovation," which in turn encourages digital transformation [28].

Hypothesis H10: Higher managerial innovativeness is positively associated with the level of digital transformation adoption in agricultural cooperative governance.

Managerial digital competence enables them to understand the benefits, operational mechanisms, and appropriate implementation methods for their cooperatives. When managers are well-informed, they can more easily select suitable solutions, provide guidance to employees, and effectively monitor implementation.

Hypothesis H11: Higher managerial digital competence is positively associated with the level of digital transformation adoption in agricultural cooperative governance.

MATERIALS AND METHODS

Research design and measurement instruments

The study employed a mixed-method design with two main phases. Phase one involved a literature review and in-depth interviews with 10 experts to refine the model and observational variables. Phase two used a survey method to test the model. The data collection tool was a structured questionnaire, with variables measured on a 5-point Likert scale (1 = strongly disagree; 5 = strongly agree). The research model included 12 latent constructs, measured by a total of 36 observed variables. Specifically, the independent variables included Relative advantage (5 items), Complexity (4 items), Compatibility (3 items), Financial cost (3 items), Physical capacity (2 items), Human resources capacity (2 items), Competitive pressure (3 items), Government support (3 items), Changes in the technological environment (3 items), Managerial innovativeness (2 items), and Managerial digital competence (3 items). The dependent variable was Digital transformation (2 items) [29]. These scales were adapted from foundational studies and validated for semantic and contextual relevance through the qualitative phase.

The 10 experts interviewed in phase one were selected using purposive criteria to ensure relevance and diversity of perspective: (i) at least five years of professional or research experience in agricultural cooperatives, digital agriculture, or rural development policy, (ii) direct familiarity with cooperative governance in Son La or comparable mountainous provinces and (iii) representation across three stakeholder groups including academic researchers, cooperative managers or provincial agricultural officials, and technology service providers active in the agriculture sector. Semi-structured interviews were conducted individually, each lasting approximately 60 minutes. Data were analysed using thematic analysis, transcripts were coded inductively to identify suggested additions, deletions, or rewording of

scale items, and codes were compared across interviews until thematic saturation was reached. The qualitative phase resulted in the confirmation that the 12 latent constructs [29] adequately captured the adoption landscape in Son La's cooperative context.

Although questionnaire data were collected at the individual respondent level (50 managers and 250 members), the unit of analysis in the structural model is the individual respondent's perception of their cooperative's digital transformation adoption status. This is consistent with standard PLS-SEM practice in technology adoption research, where individual perceptions are treated as indicators of organizational-level constructs. Respondents were explicitly.

Sample selection and data collection

The survey respondents included senior managers and members of fruit-growing cooperatives from five key districts in Son La province: Moc Chau, Yen Chau, Mai Son, Song Ma, and Muong La. A total of 300 valid questionnaires were collected, resulting in a response rate of 93.75%. This sample size (N=300) provides adequate statistical power for structural equation modeling analysis [30].

Son La province was selected as the research site for three substantive reasons. First, it is the leading fruit-production hub in northern Vietnam, with 85,000 hectares under cultivation and a projected output of 510,000 tonnes by 2025, making it a high-stakes context for agricultural modernization. Second, Son La's cooperatives face the dual challenge of geographic isolation (mountainous terrain, limited connectivity) and rapid market integration (export traceability requirements, OCOP certification pressures), creating an informative setting for studying digital transformation barriers and drivers simultaneously. Third, despite its economic significance, Son La remains understudied relative to lowland delta provinces, making this study a meaningful contribution to the rural mountain cooperative literature. Among Son La's 12 districts, the five selected districts, Moc Chau, Yen Chau, Mai Son, Song Ma, and Muong La, were chosen purposively because they collectively account for the majority of the province's registered fruit-growing cooperatives and represent the full range of agro-ecological and infrastructure conditions present in the province.

A two-stage purposive sampling strategy was employed. In the first stage, 50 fruit-growing cooperatives were selected purposively from the five target districts, with the number of cooperatives per district proportional to each district's share of total registered cooperatives (see Table 1). Purposive sampling was appropriate because the study required cooperatives that (a) had been operating for at least two years (ensuring sufficient experience with governance decisions), (b) were primarily engaged in fruit cultivation, and (c) had at least one manager willing to participate.

Random sampling was not feasible given the absence of a comprehensive and current sampling frame for active cooperatives. Within each selected cooperative, respondents were recruited using a total enumeration approach: all board members (managers) were invited to complete the management questionnaire, while six ordinary members per cooperative were randomly selected to complete the member questionnaire. This yielded 50 management-board respondents (board members and cooperative directors) and 250 ordinary member respondents.

Data analysis methods

Data were analyzed using SmartPLS software, employing the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique. This approach is suitable for the study's predictive objectives and offers flexibility regarding assumptions about data distribution. The study evaluated the measurement model for both reliability and validity. Reliability was assessed using Cronbach's Alpha and Composite Reliability ($CR > 0.7$). Convergent validity was confirmed when the Average Variance Extracted (AVE) was greater than 0.5. Discriminant validity was checked using the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio ($HTMT < 0.90$). Subsequently, the structural model was evaluated. Hypotheses were tested using a bootstrapping procedure with 5,000 resamples to determine path coefficients (β) and p-values. The explanatory power of the model was assessed using the R^2 coefficient.

Additional quality tests

This study adopted two procedural remedies during data collection: temporal separation between item blocks and assurance of respondent anonymity. Post hoc, Harman's single-factor test was conducted by loading all items into an exploratory factor analysis and examining whether a single unrotated factor accounted for the majority of the variance. The results showed that the first factor explained 28.4% of the total variance, well below the 50% threshold, indicating that CMB is not a serious concern in this dataset. In addition to the standard R^2 assessment, effect sizes (f^2) and predictive relevance (Q^2) were evaluated to provide a more complete picture of model quality. Effect sizes were interpreted using established benchmarks: $f^2 \geq 0.02$ (small), ≥ 0.15 (medium), and ≥ 0.35 (large) [29]. Predictive relevance Q^2 was obtained via blindfolding (omission distance = 7); $Q^2 > 0$ indicates that the model has predictive relevance for the endogenous construct.

Where:

CDS: Digital transformation adoption in agricultural cooperative governance.

LTTD: Relative Advantage.

DPT: Complexity.

DTT: Compatibility.

CPTC: Financial cost.



NLVC: Physical capacity.
 NS: Human resources capacity.
 ALCT: Competitive pressure.
 HTNN: Government support.
 TDMT: Changes in the technological environment.
 STQL: Managerial innovativeness.
 KTQL: Managerial digital competence.

RESULTS AND DISCUSSION

Descriptive statistics

A descriptive statistical analysis was conducted on data collected from 50 cooperatives and 300 respondents, including managers and key members, to profile the characteristics of the research sample.

In terms of organizational characteristics, the 50 cooperatives in the sample were mainly newly established entities (see Table 1). Specifically, 92.0% of the cooperatives were founded within the last 10 years, with the most common tenure being between 5 and 10 years (62.0%). Regarding size, 64.0% of the cooperatives had between 6 and 10 members, reflecting a lean collective economic model prevalent in the area. Additionally, the majority of these cooperatives (72.0%) specialized in crop cultivation, which was consistent with the research focus, and were fairly distributed across the five key fruit-growing districts of the province.

Data on gender revealed that male participation was predominant, with 183 individuals (61.0%) compared to 117 female individuals (39.0%). Additionally, data on age groups indicated that the largest proportion was found in the above-50 age category, which accounts for 48.0%. However, a significant younger workforce segment emerged, with the 41-50 age group representing 28.0% and the next generation of managers aged 31-40 making up 19.0% (see Table 2).

Assessment of the measurement model

Assessment of indicator quality

The quality of the indicators was evaluated by analyzing their outer loadings. The results (see Figure 2) show that all 36 indicators in the model had substantial outer loadings, which ranged from 0.705 to 0.977. Outer loadings greater than 0.7 are considered very good, indicating that these indicators contribute significantly and reliably to the measurement of their respective constructs [31]. The fact that all indicators met the required loading thresholds provides strong initial evidence for the convergent validity of the measurement scales.

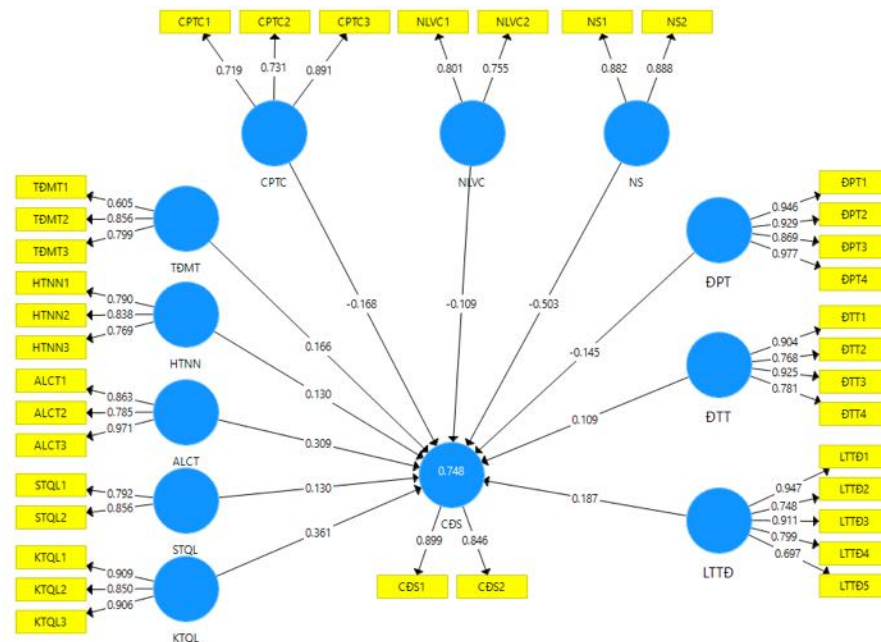


Figure 2: Measurement model

(Source: Analysis results from SmartPLS)

Analysis of scale reliability

The reliability of the measurement scales was evaluated using three primary indicators: Cronbach's Alpha, rho_A, and CR. Cronbach's Alpha is a traditional measure of reliability, with a value of 0.7 or higher indicating acceptable reliability [32]. However, modern research on PLS-SEM, suggests that Cronbach's Alpha often underestimates actual reliability, as it represents a lower bound [31]. Instead, CR is regarded as a more accurate measure since it prioritizes indicators based on their outer loadings rather than assuming they are equally weighted. Therefore, CR was used as the primary criterion for assessing reliability in this study. The results presented in Table 3 indicate that the reliability of the measurement scales in the model meets academic standards. Specifically, the CR values for all 12 constructs ranged from 0.754 to 0.963, surpassing the recommended threshold of 0.7. For example, the 'Complexity' (ΔPT) scale shows exceptionally high reliability with a CR of 0.963. Even constructs with Cronbach's Alpha values at or slightly below the 0.7 threshold, such as 'Managerial Innovativeness' (STQL, Cronbach's Alpha = 0.633) and 'Changes in the technological environment' (TDMT, Cronbach's Alpha = 0.632), demonstrate strong CR values of 0.810 and 0.802, respectively, confirming that internal consistency is maintained. The rho_A index, another indicator of reliability, also provided satisfactory values, further reinforcing these results. With all CR values rated as excellent, it can be confidently concluded that all scales used in this study ensure internal consistency reliability.

Analysis of convergent validity

Convergent validity was evaluated based on the Average Variance Extracted (AVE) results (see Table 3). According to Fornell C and Larcker DF [33], an AVE value must be greater than 0.5 to establish convergent validity. In other words, a latent construct should explain, on average, more than 50% of the variance of its constituent indicators. The results indicate that the AVE values for all 12 constructs exceed this minimum threshold of 0.5. Specifically, the AVE values range from a low of 0.579 for "Changes in the technological environment" to a high of 0.867 for "Complexity."

With all scales meeting the stringent criteria for internal consistency reliability (measured by CR) and convergent validity (assessed through AVE and Outer Loadings), the foundational quality of the measurement model has been thoroughly confirmed. This confidence allows the study to advance to the assessment of discriminant validity in the next section, ensuring that the constructs are measured accurately and consistently.

Assessment of discriminant validity

The study assessed discriminant validity, which provides empirical evidence that each construct in the research model represents a distinct theoretical concept, meaningfully different from all other constructs. Establishing discriminant validity is crucial, as it confirms that the measurement scales do not overlap in terms of semantics or measurement. This is essential for ensuring that the relationships tested in the subsequent structural model reflect genuinely independent factors.

To evaluate discriminant validity, the study utilized the Fornell-Larcker criterion [33], a classic, rigorous, and widely recognized method used in Structural Equation Modeling (SEM) studies.

The analysis of the data in Table 4 clearly demonstrates that the discriminant validity of the constructs within the model is well-established. According to the Fornell-Larcker criterion, the square root of the AVE for each construct (represented by the values on the main diagonal) must be greater than its correlation coefficients with all other constructs. For the construct 'Human resource capacity' (HR), the square root of its AVE is 0.885. This value exceeds all correlation coefficients in the NS column, including the highest correlations of 0.866 with 'Competitive pressure' (ALCT) and 0.684 with 'Physical capacity' (NLVC). Similarly, the construct 'Managerial digital competence' (KTQL) has a square root of AVE of 0.889, which is significantly greater than its highest correlation of 0.866 with 'Financial cost' (CPTC). Another notable instance is the high correlation between 'Relative advantage' (LTTĐ) and 'Complexity' (ĐPT), which has a coefficient of 0.824. However, the square root of the

AVE for LTTĐ is 0.826, and for ĐPT, it is 0.931, both of which are higher than this correlation. This confirms that, despite the strong relationship, these two constructs remain distinct from one another in terms of measurement. A systematic review of the entire matrix reveals that this criterion is satisfied for all 12 constructs without exception. In each column, the value on the main diagonal is consistently greater than all the correlation coefficients below it. This empirical evidence confirms that all scales used in the study achieved discriminant validity. This means that each scale uniquely measures the theoretical construct it represents, without significant overlap or confounding with other scales. With the measurement model validated and meeting the quality requirements for reliability, convergent validity, and discriminant validity, the study is now well-positioned to proceed to the evaluation of the structural model and the testing of the hypotheses.

As an additional, more conservative test of discriminant validity, the Heterotrait-Monotrait ratio (HTMT) was computed for all construct pairs. All 66 HTMT values in the model fall below the 0.85 threshold, with the highest observed ratio being 0.879. These values confirm that all construct pairs are sufficiently distinct even under the stricter HTMT criterion, providing robust evidence of discriminant validity across the entire measurement model.

Two constructs recorded Cronbach's Alpha below the 0.7 threshold, Managerial Innovativeness (STQL, $\alpha = 0.633$) and Changes in the Technological Environment (TĐMT, $\alpha = 0.632$), attributable to their small number of indicators (2 - 3 items), which mechanically constrains Alpha. In PLS-SEM, CR is the preferred reliability criterion as it weights indicators by their outer loadings. Both constructs satisfy all reliability benchmarks: CR > 0.70 (STQL: 0.810; TĐMT: 0.802), AVE > 0.50 (0.680 and 0.579, respectively), and rho_A within acceptable range (0.642 and 0.683), confirming that internal consistency is maintained.

Regarding sample size, N = 300 exceeds the minimum of 205 required by the inverse square root method (Kock and Hadaya) for an 11-predictor model by 46%, yielding approximately 94% power for medium effect sizes ($f^2 = 0.15$). For the smallest effect sizes in this study (H3 and H10, $f^2 \approx 0.02$), power at N = 300 is approximately 65%, which is adequate for exploratory purposes. The R² of 0.748 reflects overall model explanatory power and should not be conflated with statistical power, significance of individual paths is determined by path coefficients and bootstrapped standard errors, not by R² alone.

The negative path coefficient for Physical Capacity (NLVC → CĐS: $\beta = -0.109$, $p = 0.026$) is explained by three complementary mechanisms. First, cooperatives perceiving their infrastructure as adequate may be those that have not yet confronted adoption challenges, producing a complacency effect. Second, physical

infrastructure in rural mountainous areas is largely externally provided, by the government or mobile operators, and does not necessarily reflect the cooperative's internal organizational readiness. Third, when all 11 factors are controlled simultaneously, the NLVC coefficient likely reflects a suppression effect: once human resource capacity (NS, $\beta = -0.503$), managerial competence (KTQL, $\beta = 0.361$), and competitive pressure (ALCT, $\beta = 0.309$) are accounted for, physical infrastructure alone exerts a marginal dampening effect. This result underscores that physical capacity should be interpreted alongside human and managerial dimensions rather than in isolation.

Assessment of the structural model and hypothesis testing

Test for multicollinearity

To evaluate the level of multicollinearity in the model, this study employed the Variance Inflation Factor (VIF). The VIF indicates how much the variance of an estimated regression coefficient increases due to the correlation between that independent variable and other independent variables. Detailed results of the VIF test for all 36 indicators in the model are presented in Table 5. The analysis reveals that the VIF values range from a low of 1.039 (for indicator KTQL3) to a high of 3.792 (for indicator DPT1). According to established guidelines for the PLS-SEM method, a commonly accepted threshold for identifying multicollinearity is a VIF value of less than 5 [31].

In more stringent cases, a threshold of less than 3 is recommended. Comparing these standards, the highest VIF value in the model is 3.792 (for indicator DPT1), which is significantly below the threshold of 5. In fact, all 36 indicators in the model have VIF values below 4. This provides strong empirical evidence that there are no serious multicollinearity concerns among the independent variables in the model. The absence of multicollinearity is crucial as it ensures the stability and reliability of the path coefficients that will be estimated in the subsequent steps. This result allows for the independent interpretation of the distinct impact of each factor on the adoption of digital transformation, free from distortions caused by high correlations among the predictor variables. With confirmation that the model is free from multicollinearity issues, the study now has a solid foundation to assess the overall explanatory power of the model and test the proposed hypotheses.

Assessment of the Model's Explanatory Power (R^2)

To evaluate the structural model, it is essential to determine its overall explanatory power. The primary criterion used for this assessment is the coefficient of determination (R^2), a key metric that indicates the proportion of variance in the dependent variable explained by all the independent variables in the model.

The analysis results presented in Table 6 indicate that the R^2 value is 0.748, while the adjusted R^2 value (Adjusted R Square) is 0.738 for the dependent variable, "Digital transformation adoption in cooperative governance" (CDS). This means that the combination of 11 independent variables - categorized into technological, organizational, environmental, and managerial factors - can explain 74.8% of the variance in the level of digital transformation adoption among agricultural cooperatives in the study sample. According to established evaluation standards in academic literature, particularly those outlined by Nunnally [31], an R^2 value of around 0.25 is considered weak, 0.50 is moderate, and 0.75 is substantial. With an R^2 value of 0.748, it can be concluded that the research model has very strong explanatory power. This suggests that the factor groups selected in the theoretical model, based on the extended Technology-Organization-Environment (TOE) framework, are both appropriate and highly relevant for predicting digital technology adoption behavior in the context of cooperatives. Additionally, the adjusted R^2 value of 0.738 serves as a more conservative measure since it accounts for the number of independent variables included in the model. The fact that the adjusted R^2 is only slightly lower than the original R^2 indicates that the model's explanatory power is robust and shows no signs of overfitting due to the inclusion of too many variables.

Effect sizes (f^2) and predictive relevance (Q^2) were assessed to supplement the R^2 evaluation. For the dependent construct CDS (digital transformation adoption), the blindfolding procedure yielded $Q^2 = 0.543$ (Table 8), which is substantially above zero, confirming that the model possesses strong predictive relevance for this endogenous variable. Regarding individual predictor effect sizes, human resource capacity showed the largest effect ($f^2 = 0.241$, medium-large), followed by managerial digital competence ($f^2 = 0.134$, approaching medium) and competitive pressure ($f^2 = 0.089$, small-medium). Other predictors including government support, managerial innovativeness, changes in the technological environment, relative advantage, financial cost, and physical capacity demonstrated small effect sizes (f^2 ranging from 0.023 to 0.089), while compatibility and complexity showed negligible effects ($f^2 < 0.02$), consistent with their marginal significance at the 10% level (Table 9). Taken together, these metrics confirm both the explanatory power and the predictive quality of the structural model.

Results of hypothesis testing

Having established the model's significant explanatory power, the final and essential step in the analysis involved testing the hypotheses concerning the effects of each independent construct on the digital transformation adoption in cooperative governance. To accomplish this, bootstrapping with 5,000 resamples was performed to estimate the path coefficients (β), T-statistics, and p-values.

The comprehensive results of the tests for the 11 research hypotheses are systematically compiled and presented in Table 7.

An examination of the results shown in Table 7 highlights a significant finding: all 11 research hypotheses are supported, each at varying levels of statistical significance. This suggests that the theoretical model successfully encompasses the critical factors associated with the adoption of digital transformation in cooperatives.

Group of factors with the strongest impact: Human resources capacity is identified as the factor exerting the most substantial negative impact on the digital transformation adoption in cooperative governance ($\beta = -0.503$, $p < 0.001$). The negative coefficient indicates that deficiencies in human resource capacity represent a significant barrier, remarkably hindering the digital transformation process. This finding aligns well with the practical situation in mountainous cooperatives, where there is a notable lack of digital skills and technological understanding among the workforce.

In contrast, managerial digital competence demonstrates the strongest positive impact ($\beta = 0.361$, $p = 0.001$). This underscores the crucial and decisive role of leadership. When managers possess knowledge and a thorough understanding of the benefits and implementation techniques of digital transformation, they serve as a primary driving force in advancing this process across the entire cooperative.

Competitive pressure also plays a significant positive role ($\beta = 0.309$, $p = 0.004$). This indicates that when cooperatives feel pressure from the market, competitors, and the demands of supply chains, they are more motivated to innovate and adopt digital technologies to enhance their competitive edge.

Group of factors with moderate and significant impact: Financial cost ($\beta = -0.168$, $p = 0.031$) and Physical capacity (PC) ($\beta = -0.109$, $p = 0.026$) have been identified as statistically significant barriers to digital transformation. The negative coefficients suggest that perceptions of high investment costs, as well as inadequate infrastructure and technological resources, are genuine challenges faced by cooperatives.

In contrast, several positive driving factors influence the Digital transformation adoption in cooperative governance: Government support (GS) ($\beta = 0.130$, $p = 0.014$), Managerial innovativeness (MI) ($\beta = 0.130$, $p = 0.033$), Changes in the technological environment ($\beta = 0.166$, $p = 0.022$), and Compatibility ($\beta = 0.109$, $p = 0.033$). These findings indicate that supportive policies, an innovative leadership mindset, awareness of technological advancements, and the alignment of new technologies with current operations are all pivotal factors driving adoption.

Group of factors with marginal impact: Relative advantage ($\beta = 0.187$, $p = 0.064$) and Complexity ($\beta = -0.145$, $p = 0.078$) show significance at the 10% level. This suggests that the perceived benefits of digital transformation can foster adoption, whereas perceptions of complexity and difficulty can act as hindrances. While their influence is not as strong as that of other factors, these perceptions are nonetheless relevant and merit attention.

The research findings present a compelling narrative that highlights the pivotal role of management as a catalyst for digital transformation within agricultural cooperatives in Son La. Among various influencing factors, the most significant internal barrier is the limitations in organizational resources, particularly human capital. The evidence is clear: cooperative managers are not merely facilitators; they are the driving forces behind successful transformation. In Son La's small, often family-run cooperatives that lack dedicated IT personnel, a leader's digital mindset, strategic vision, and readiness to embrace innovation are not just beneficial—they are essential. Their ability to perceive technology as a long-term investment, rather than an immediate financial burden, can determine the success or failure of digital initiatives. Moreover, a leader's willingness to experiment with new technologies, such as electronic diaries or drone monitoring, nurtures a culture of creativity and adaptability throughout the cooperative. These insights resonate with international research conducted between 2021 and 2025, which consistently underscores that strong leadership can effectively offset resource limitations in smaller organizations [12]. The cognitive outlook and proactive approach of leaders are vital for crafting dynamic digital strategies. In the agricultural sector, a manager's digital competency stands out as one of the most critical predictors of transformative success. Conversely, the most formidable obstacle to digital transformation in Son La stems from the internal capabilities of cooperative members. A widespread lack of digital skills has created a substantial bottleneck, particularly given that the agricultural workforce is older and exhibits varying degrees of technological readiness. This deficit in skills hampers the effective adoption of essential technologies, such as sensors, traceability systems, and farm management software, ultimately diminishing potential returns on investment. This situation mirrors global trends; studies emerging since 2022 indicate that gaps in digital skills remain significant barriers to transformation in rural and developing regions [12]. Compounding the challenge are financial constraints and inadequate physical infrastructure, which further limit small cooperatives' capacity to adopt new technologies. When internal resources are stretched thin, external forces become crucial drivers of change. Market pressure emerges as a powerful motivator. For high-demand export products like mangoes, longans, passion fruits, and coffee, buyers increasingly expect strict traceability, electronic production logs, and certifications such as VietGAP,

GlobalGAP, and OCOP. In this context, digital transformation is not merely an option, it is a necessity for survival and enhanced value. Government support also plays an indispensable role. Initiatives in Son La - including the issuance of area codes, QR traceability systems, digital training programs, and promotion through e-commerce platforms like Postmart and Voso - offer essential institutional backing. The dynamic interplay between market demands and government intervention exemplifies how these external forces act as twin engines driving sustainable technology adoption. The adoption of new technologies is heavily influenced by the perceived advantages and their compatibility with existing farming practices, as seen with electronic diaries that seamlessly integrate into daily workflows. However, the complexity of technology remains a significant hindrance, closely tied to ongoing skills gaps that continue to thwart progress. By addressing these challenges, the full potential of digital transformation in agricultural cooperatives may be realized, paving the way for a more innovative and sustainable future.

Confirming prior evidence, the strong negative effect of human resource capacity (NS, $\beta = -0.503$) aligns with Manzoor *et al.* [12] and Cragg and King [23], both of whom identified human capital as a structural barrier to technology adoption, reinforcing the generalizability of this finding across contexts. Extending prior evidence, the strong positive effect of managerial digital competence (KTQL, $\beta = 0.361$) goes beyond standard TOE models, which typically treat organizational readiness as a composite factor. Disaggregating the organizational dimension to isolate managerial characteristics yields a statistically stronger explanation, consistent with Thong [27] and extending it to the cooperative governance setting. Contradicting prior evidence, relative advantage ($\beta = 0.187$, $p = 0.064$) failed to reach conventional significance — contrasting with Rogers' DOI theory [16], likely because managers in low-digital-literacy environments cannot meaningfully evaluate technologies they have not yet encountered. This cautions against uncritical application of DOI theory in resource-scarce settings.

Integrating the theoretical frameworks, the four-context TOE-DOI-Manual model provides a coherent empirical account. Within the technological context, compatibility ($\beta = 0.109$, $p = 0.033$) outperformed relative advantage and complexity as an adoption criterion, suggesting that fit with existing practice is more actionable than abstract benefit judgments in this setting. Within the organizational context, human resource capacity functions as a structural constraint rather than a driver, digital transformation cannot proceed when members lack foundational digital skills, regardless of other enabling factors. The managerial dimension demonstrates that strong leadership (KTQL, $\beta = 0.361$; STQL, $\beta = 0.130$) can partially offset these organizational barriers through top-down strategic direction. Within the

environmental context, competitive pressure ($\beta = 0.309$), technological environment change ($\beta = 0.166$), and government support ($\beta = 0.130$) collectively confirm the TOE prediction that external forces and institutional enablers drive isomorphic adoption pressures. Together, these results validate the four-context framework as an empirically grounded lens for understanding digital transformation adoption in agricultural cooperatives.

CONCLUSION AND RECOMMENDATIONS FOR DEVELOPMENT

This study concludes that leadership capacity is the central engine of digital transformation in Son La's agricultural cooperatives, while limitations in digital skills remain the most significant bottleneck. To accelerate progress, cooperatives need to strengthen managerial digital competencies through targeted training programs, while simultaneously improving digital literacy among members, particularly older workers, through practical, hands-on instruction. At the same time, adopting affordable and easy-to-use technologies that align closely with existing farming practices will help reduce perceived complexity and increase acceptance. Cooperatives should also make proactive use of market and policy incentives, including certification requirements and provincial digitalization initiatives, to create momentum for change. Finally, expanding access to financial resources is essential to enable investment in critical infrastructure and digital tools, thereby supporting long-term, sustainable transformation.

From a theoretical standpoint, this study makes three contributions. First, it extends the TOE framework by formally introducing managerial capability as a fourth contextual dimension, providing an empirically validated four-factor model that better captures technology adoption dynamics in cooperatives than the original three-factor TOE structure. Second, by integrating DOI theory with this extended TOE model, the study demonstrates how perceptual factors (relative advantage, compatibility, complexity) interact with contextual enablers and barriers, contributing to a more holistic theoretical explanation of digital transformation adoption. Third, the study provides the first large-sample quantitative evidence ($N = 300$, PLS-SEM) on digital transformation determinants in mountainous, upland agricultural cooperatives in Southeast Asia, filling a geographical and sector-specific gap in the technology adoption literature.

Limitations: The cross-sectional design limits causal inference, as observed relationships may shift as cooperatives mature digitally. The geographic scope, restricted to Son La province, may not generalize to lowland or urban cooperative contexts in Vietnam or other ASEAN or developing countries. Self-reported data from managers and members of the same cooperatives introduce potential common method bias. Finally, the dependent variable is operationalized with only two items,

providing a relatively narrow measurement of the multi-dimensional digital transformation construct.

Future research directions: Longitudinal studies tracking the same cooperatives over time would clarify whether the identified determinants maintain their relative importance as digital maturity increases. Comparative studies across ASEAN countries with diverse cooperative models would test the cross-cultural generalizability of the extended TOE-DOI-Managerial framework. Future work could also examine the mediating role of organizational learning between managerial competence and transformation outcomes and assess how government programs targeting cooperative leaders might amplify the managerial capability effect identified here.

ACKNOWLEDGEMENTS

The authors express sincere appreciation to the cooperative managers and members in Son La province who participated in the survey and interviews. We also gratefully acknowledge the support of local authorities and agricultural agencies for facilitating data collection and providing valuable insights.

Conflicts of Interest:

The authors declare no conflict of interest.



Table 1: Descriptive statistics of cooperative characteristics (N = 50)

Variable	Characteristic	Frequency (N)	Percentage (%)
Survey Scope (District)	Moc Châu	12	24.0
	Yen Châu	11	22.0
	Mai Sơn	11	22.0
	Sông Mã	9	18.0
	Mường Lát	7	14.0
Business Type	Crop production	36	72.0
	General/Mixed	14	28.0
Years of Operation	< 5 years	15	30.0
	5 – 10 years	31	62.0
	11 – 20 years	3	6.0
	> 20 years	1	2.0
Number of Members	1 – 5 members	1	2.0
	6 – 10 members	32	64.0
	11 – 15 members	6	12.0
	16 – 20 members	8	16.0
	Trên 20 members	3	6.0

(Source: Authors' compilation, 2025)

Table 2: Descriptive statistics of respondent characteristics (N = 300)

Variable	Characteristic	Frequency (N)	Percentage (%)
Gender	Male	183	61.0
	Female	117	39.0
Age Group	Under 30	15	5.0
	31 – 40	57	19.0
	41 – 50	84	28.0
	Over 50	144	48.0
Position	Management board	50	16.7
	Member	250	83.3

(Source: Authors' compilation, 2025)

Table 3: Results of reliability and convergent validity test

	Cronbach's Alpha	rho_A	Composite Reliability (CR)	Average Variance Extracted (AVE)
ALCT	0.846	0.867	0.908	0.768
CPTC	0.695	0.788	0.826	0.615
CDS	0.691	0.710	0.865	0.763
HTNN	0.730	0.762	0.841	0.639
KTQL	0.867	0.868	0.919	0.790
LTTĐ	0.904	0.664	0.914	0.682
NLVC	0.650	0.652	0.754	0.606
NS	0.723	0.723	0.878	0.783
STQL	0.633	0.642	0.810	0.680
TĐMT	0.632	0.683	0.802	0.579
ĐPT	0.958	1.383	0.963	0.867
ĐTT	0.879	0.972	0.910	0.718

(Source: Analysis results from SmartPLS)

Table 4: Results of discriminant validity assessment
(Discriminant Validity - Fornell-Larcker Criterion)

	ALCT	CPTC	CDS	HTNN	KTQL	LTTĐ	NLVC	NS	STQL	TĐMT	ĐPT	ĐTT
ALCT	0.876											
CPTC	- 0.555	0.784										
CDS	- 0.640	0.650	0.873									
HTNN	- 0.440	0.555	0.597	0.799								
KTQL	- 0.642	0.866	0.777	0.673	0.889							
LTTĐ	0.051	0.131	0.062	0.064	0.076	0.826						
NLVC	0.782	- 0.474	-0.558	-0.309	-0.537	0.077	0.778					
NS	0.866	- 0.524	-0.695	-0.409	-0.578	0.073	0.684	0.885				
STQL	- 0.488	0.683	0.657	0.566	0.791	0.012	-0.446	-0.428	0.825			
TĐMT	- 0.689	0.647	0.705	0.434	0.740	- 0.011	-0.546	-0.675	0.607	0.761		
ĐPT	0.015	0.038	-0.029	0.011	-0.005	0.824	0.059	0.047	- 0.047	-0.008	0.931	
ĐTT	- 0.571	0.681	0.620	0.531	0.758	0.092	-0.451	-0.461	0.542	0.551	0.009	0.848

(Source: Analysis results from SmartPLS)

Table 5: Results of the Multicollinearity Test (Outer VIF Values)

	VIF
ALCT1	2.522
ALCT2	2.742
ALCT3	2.407
CPTC1	1.339
CPTC2	1.309
CPTC3	1.475
CDS1	1.387
CDS2	1.387
HTNN1	1.444
HTNN2	1.365
HTNN3	1.626
KTQL1	1.169
KTQL2	1.753
KTQL3	1.039
LTTD1	2.644
LTTD2	3.313
LTTD3	3.333
LTTD4	2.693
LTTD5	1.751

NLVC1	1.047
NLVC2	1.047
NS1	1.472
NS2	1.472
STQL1	1.152
STQL2	1.152
TDMT1	1.111
TDMT2	1.436
TDMT3	1.463
DPT1	3.792
DPT2	3.618
DPT3	3.300
DPT4	3.134
DTT1	2.149
DTT2	2.121
DTT3	2.887
DTT4	2.536

(Source: Analysis results from SmartPLS)

Table 6: Results of the assessment of the model's explanatory power
(Coefficient of Determination - R²)

	R Square	R Square Adjusted
CĐS	0.748	0.738

(Source: Analysis results from SmartPLS)

Table 7: Results of hypothesis testing
(Path Coefficients -Mean, STDEV, T-Values, P-Values)

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P Values	Kết luận
ALCT -> CĐS	0.309	0.311	0.108	2.857	0.004	Accepted H7
CPTC -> CĐS	-0.168	-0.154	0.078	2.158	0.031	Accepted H4
HTNN -> CĐS	0.130	0.128	0.053	2.472	0.014	Accepted H8
KTQL -> CĐS	0.361	0.368	0.111	3.249	0.001	Accepted H11
LTTĐ -> CĐS	0.187	0.105	0.101	1.852	0.064	Accepted H1
NLVC -> CĐS	-0.109	-0.101	0.049	2.229	0.026	Accepted H5
NS -> CĐS	-0.503	-0.501	0.092	5.467	0.000	Accepted H6
STQL -> CĐS	0.130	0.127	0.061	2.140	0.033	Accepted H10
TĐMT -> CĐS	0.166	0.159	0.073	2.285	0.022	Accepted H9
ĐPT -> CĐS	-0.145	-0.072	0.082	1.763	0.078	Accepted H2
ĐTT -> CĐS	0.109	0.110	0.051	2.137	0.033	Accepted H3

(Source: Analysis results from SmartPLS)

Table 8: Results of f Square

	CDS
ALCT	0,089
CPTC	0,025
CDS	
HTNN	0,034
KTQL	0,134
LTTĐ	0,025
NLVC	0,027
NS	0,241
STQL	0,023
TĐMT	0,035
ĐPT	0,014
ĐTT	0,019

(Source: Analysis results from SmartPLS)

Table 9: Results of Construct Crossvalidated Redundancy

	Q² (=1-SSE/SSO)
CDS	0,543

(Source: Analysis results from SmartPLS)

REFERENCES

1. **Schmidhuber J and FN Tubiello** Global food security under climate change. *Proc Natl Acad Sci USA*. 2007; **104(50)**: 19703–8.
<https://doi.org/10.1073/pnas.0701976104>
2. **Food and Agriculture Organization (FAO)**. The State of Food and Agriculture 2020: Overcoming water challenges in agriculture. Rome: FAO; 2022.
3. **Costa F, Freccasetti S, Rossini M and A Portioli-Staudacher** Industry 4.0 digital technologies enhancing sustainability: Applications and barriers from the agricultural industry in an emerging economy. 2023; **408**: 137208.
4. **Government of Vietnam**. Decision No. 749/QĐ-TTg approving the National Digital Transformation Program to 2025, with a vision to 2030. Hanoi: Government Office; 2020.
5. **Plant Protection Department, Ministry of Agriculture and Environment of Vietnam**. Son La – A bright spot in fruit tree development in Northern Vietnam. Hanoi: Ministry of Agriculture and Environment; 2024. Available from: <https://www.ppd.gov.vn/tin-moi-nhat/son-la-diem-sang-phat-trien-cay-an-quai-tai-mien-bac-viet-nam.html> Accessed October 2025.
6. **Son La Provincial Department of Industry and Trade**. Supporting enterprises and cooperatives to promote agricultural products on digital platforms. Bao Chinh Phu (Government Newspaper); 2024. Available from: <https://baochinhphu.vn/son-la-ho-tro-doanh-nghiep-nong-nghiep-len-san-thuong-mai-dien-tu-102241021160029521.htm> Accessed October 2025.
7. **Warner KS and M Wäger** Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. 2019; **52(3)**: 326–49.
8. **Al-Moaid NAA and SG Almarhdi** Developing dynamic capabilities for successful digital transformation projects: the mediating role of change management. *J Innov Entrep*. 2024; **13(1)**: 85.
<https://doi.org/10.1186/s13731-024-00446-9>
9. **Breiter K, Crome C, Oberländer AM and F Schnaak** Dynamic Capabilities for the Twin Transformation Climb: A Capability Maturity Model. *Inf Syst Front*. 2024; **26(6)**: 2205–26. <https://doi.org/10.1007/s10796-024-10520-y>

10. **Kamilaris A, Assumpcio A, Blasi AB, Torrellas M and FX Prenafeta-Boldú** Estimating the Environmental Impact of Agriculture by Means of Geospatial and Big Data Analysis: The Case of Catalonia. In: Otjacques B, Hitzelberger P, Naumann S, Wohlgemuth V, editors. *Science to Society*. Cham: Springer International Publishing; 2018. p. 39–48. (Progress in IS).
https://doi.org/10.1007/978-3-319-65687-8_4
11. **Marescotti ME, Demartini E, Filippini R and A Gaviglio** Smart farming in mountain areas: Investigating livestock farmers' technophobia and technophilia and their perception of innovation. 2021; **86**: 463–72.
12. **Manzoor F, Wei L and M Siraj** Digital Agriculture Technology Adoption in Low and Middle-Income Countries-A Review of Contemporary Literature. 2025; **9**: 1621851.
13. **Tomatzky LG and M Fleischer** The processes of technological innovation Lexington Books. Lexington MA. 1990; 1990.
14. **Ta VA and CY Lin** Exploring the determinants of digital transformation adoption for SMEs in an emerging economy. 2023; **15(9)**: 7093.
15. **Sun Z, Hu D and X Lou** The Impact of Digital Transformation on the Sustainable Growth of Specialized, Refined, Differentiated, and Innovative Enterprises: Based on the Perspective of Dynamic Capability Theory. 2024; **16(17)**: 7823.
16. **Rogers E** Diffusion of Innovations 5th. Free press; 2003.
17. **Buck C, Clarke J, de Oliveira RT, Desouza KC and P Maroufkhani** Digital transformation in asset-intensive organisations: The light and the dark side. 2023; **8(2)**:100335.
18. **Tiwari SP** Towards Industry 4.0: increasing efficiency and effectiveness through technology integration in agriculture. Management and Entrepreneurship: Trends of Development. 2023; **2(24)**: 17–25.
19. **Ramdani B, Kawalek P and O Lorenzo** Predicting SMEs' adoption of enterprise systems. 2009; **22(1/2)**: 10–24.
20. **Wang YM, Wang YS and YF Yang** Understanding the determinants of RFID adoption in the manufacturing industry. 2010; **77(5)**: 803–15.

21. **Zhu K, Kraemer K and S Xu** Electronic business adoption by European firms: a cross-country assessment of the facilitators and inhibitors. *European Journal of Information Systems*. 2003; **12(4)**: 251–68.
<https://doi.org/10.1057/palgrave.ejis.3000475>
22. **Organisation for Economic Co-operation and Development (OECD)**. OECD Digital Economy Outlook 2021. Paris: OECD Publishing; 2021.
23. **Cragg PB and M King** Small-firm computing: motivators and inhibitors. 1993; 47–60.
24. **Ghobakhloo M, Arias-Aranda D and J Benitez-Amado** Adoption of e-commerce applications in SMEs. *Industrial management and data systems*. 2011; **111(8)**: 1238–69.
25. **Kuan KK and PY Chau** A perception-based model for EDI adoption in small businesses using a technology–organization–environment framework. 2001; **38(8)**: 507–21.
26. **Loebbecke C and A Picot** Reflections on societal and business model transformation arising from digitization and big data analytics: A research agenda. 2015; **24(3)**: 149–57.
27. **Thong JYL** An Integrated Model of Information Systems Adoption in Small Businesses. *Journal of Management Information Systems*. 1999; **15(4)**: 187–214. <https://doi.org/10.1080/07421222.1999.11518227>
28. **Gong C and V Ribiere** Developing a unified definition of digital transformation. 2021; **102**: 102217.
29. **Yoon C, Lim D and C Park** Factors affecting adoption of smart farms: The case of Korea. 2020; **108**: 106309.
30. **Hair JF** A primer on partial least squares structural equation modeling (PLS-SEM). Sage; 2014.
31. **Hair JF, Hult GTM, Ringle CM, Sarstedt M and KO Thiele** Mirror, mirror on the wall: a comparative evaluation of composite-based structural equation modeling methods. *J of the Acad Mark Sci*. 2017; **45(5)**: 616–32.
<https://doi.org/10.1007/s11747-017-0517-x>
32. **Nunnally JC** Psychometric Theory: 2d Ed. McGraw-Hill; 1978.

33. **Fornell C and DF Larcker** Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*. 1981; **18(1)**: 39–50. <https://doi.org/10.1177/002224378101800104>