

Modeling Farmers' Behavioral Intention to Adopt Digital Technologies in Primary Cambodian Agricultural Hubs

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ABSTRACT

As Cambodia advances its digital agricultural ecosystem under national strategic policy frameworks, understanding farmers' adoption of digital agricultural technologies Modeling Farmers' Behavioral Intention to Adopt Digital Technologies in Primary Cambodian Agricultural Hubs is critical for inclusive rural development. This study evaluates the structural determinants influencing farmers' behavioral intention to adopt digital agricultural tools using an adapted Unified Theory of Acceptance and Use of Technology (UTAUT) framework. Empirical data were collected from a sample of 400 gender-balanced farmers across ten districts in eight primary paddy rice and vegetable producing provinces. Following a two-stage scale purification process that reduced an initial 86-item pool to 30 finalized indicators, latent constructs were evaluated using Partial Least Squares Structural Equation Modeling (PLS-SEM) in JASP (version 0.19.2) with z-score standardization.

The structural model accounted for 32.9% of the variance in behavioral intention ($R^2 = 0.329, R^2_{adj} = 0.322, Q^2 = 0.209$). Performance expectancy emerged as the sole statistically significant positive predictor ($\beta = 0.240, p < .001$), indicating that farmers prioritize tangible economic gains, operational cost reductions, and yield improvements. Conversely, general digital literacy ($\beta = -0.002, p = .962$) and structural readiness ($\beta = -0.025, p = .499$) showed no statistically significant direct association with adoption intent, demonstrating that deep agronomic experience and household delegation offset digital literacy friction and that infrastructural constraints do not diminish underlying psychological motivation. Social influence exhibited a non-significant trend toward positive association ($\beta = 0.190, p = .058$) under a prespecified $\alpha = .05$ significance threshold, reflecting fragmented agricultural cooperative membership.

These findings suggest that digital agricultural interventions should reorient messaging toward explicit financial utility while leveraging cooperative networks and commune agriculture officers for localized extension services.

Keywords: Performance Expectancy, UTAUT, PLS-SEM, Technology Adoption, Scale Standardization.

BACKGROUND AND LITERATURE REVIEW

Agriculture remains a fundamental pillar of Cambodia's economic development, with the sector projected to grow by 0.9% in 2025, propelled by favorable climatic conditions and expanding export demand (ADB, 2026).

However, deep-seated systemic vulnerabilities continue to suppress long-term structural productivity across the value chain. High input and electricity costs, underdeveloped post-harvest processing infrastructure, and restricted access to affordable credit (ADB, 2021) further compound this economic stagnation.

Digital transformation offers a viable pathway to alleviate structural impediments in the agricultural sector. Cutting-edge technologies including remote sensing, satellite imaging, Geographic Information Systems (GIS), and Artificial Intelligence (AI) can optimize water management, forecast weather disruptions, and diagnose crop diseases, while mobile infrastructure and distributed computing eliminate geographic exclusion by directly connecting smallholders to markets and finance (USAID, 2018). Recognizing this potential, the Royal Government of Cambodia has elevated "Technology" as a core pillar under the Pentagonal Strategy Phase I. Aligned with the Digital Economy and Society Policy Framework 2021–2035, this policy matrix positions digital integration as a primary driver of agricultural modernization and economic diversification (RGC, 2023). Consequently, state and development agencies are actively piloting public-private digital initiatives, ranging from national agricultural base registries, such as *FarmBook*, to localized marketplace applications and digital trade platforms (Banga et al., 2020; Montesclaros & Teng, 2023).

Despite these macro-level institutional and infrastructural investments, a critical execution gap hampers the sector. While mobile coverage and basic connectivity have expanded rapidly across rural areas, the actual adoption intensity and sustained use of specialized digital agriculture tools among Cambodian farmers remain highly localized and low (Thi Hoa Sen et al., 2024). Rural producers frequently default to traditional, informal information networks and familiar interpersonal channels (Nickens et al., 2023), leaving expensive digital extension and marketplace infrastructures severely underutilized (Chan et al., 2020).

To address this disconnect, extension programs and software designers often operate on the assumption that technical complexity, low formal education, and cellular infrastructure deficits are the primary barriers to adoption, channeling substantial resources into user interface simplification and basic onboarding. However, this operational assumption neglects the economic, internal cognitive, and psychological decision-making processes of resource-constrained farmers. Crucially, minimal research has empirically investigated these internal behavioral frameworks within farmer contexts (Deichmann et al., 2016; Iskandar & Gatzweiler, 2014; Maddison, 2007a; Mastenbroek et al., 2021). It remains unclear whether reducing technical friction actually drives adoption intent, or whether farmers' willingness to integrate digital tools is strictly governed by economic calculus. Because the realized macro-benefits of Agri-Tech such as data-driven sustainability, precision farming, and enhanced food security (Gabriel & Gandorfer, 2023) are entirely contingent upon widespread stakeholder adoption (Geng et al., 2024), empirically evaluating the cognitive and economic factors governing tool acceptance is vital.

The Unified Theory of Acceptance and Use of Technology (UTAUT) framework is used in this study to systematically investigate the behavioral drivers and adoption patterns of farmers with respect to novel digital applications. The UTAUT framework, based on a comprehensive synthesis of foundational technology acceptance literature, provides a powerful and highly integrated mechanism for understanding how farmers, who often operate with limited resources, assess digital interventions. By isolating the distinct dimensions of utility, ease of use, social environments, and structural infrastructure, this framework provides a granular diagnostic lens that is well-suited to examine agricultural modernization within developing economies.

Theoretical Rationale of UTAUT Selection

The Technology Acceptance Model (TAM) has long served as the dominant lens for explaining individual technology adoption, positing that perceived usefulness and perceived ease of use jointly shape attitude toward using a system and, in turn, behavioral intention and actual use (Davis, 1989). Building on this foundation, Venkatesh et al. (2003) proposed the UTAUT, synthesizing eight competing models into four core constructs: performance expectancy, General Digital Literacy, social influence, and facilitating conditions. In their validation studies, this integrated model accounted for approximately 70% of the variance in behavioral intention, markedly exceeding the 17–41% explained by its constituent predecessor models. It is this gain in explanatory power that subsequent reviews most frequently cite as justification for treating UTAUT as the more comprehensive successor to TAM, although replication studies have since reported more variable figures,

ranging from approximately 35% to 65%, suggesting the magnitude of UTAUT's advantage is context-dependent rather than fixed.

More consequential than the variance statistic, however, is the theoretical mechanism that differentiates the two models in low-resource settings. Where TAM implicitly assumes that the infrastructure required to act on usefulness and ease-of-use perceptions is already in place, UTAUT's facilitating-conditions construct explicitly measures whether users believe the organizational and technical support needed to use a system actually exists. This distinction becomes analytically decisive once resource constraints are introduced. Zhang et al. (2024), for instance, argue that the agricultural sector's unique context necessitates a comprehensive model such as UTAUT precisely because adoption barriers among smallholders are as much structural as cognitive. This position is reinforced by Mkunda (2025), whose study of cold-chain technology adoption among Tanzanian vegetable producers' frames facilitating conditions as indispensable in low-resource agricultural settings, given that such technologies demand infrastructure, capital, and training that cannot be assumed present. Similarly, Ravindran et al. (2024) conclude, in their review of smart-farming technology adoption in Malaysia, that facilitating conditions are especially important for smallholder farmers relative to other user populations.

A second construct, social influence, has also been advanced as better suited to the collectivist, community-embedded decision-making that often characterizes smallholder and rural households, a dynamic that TAM's individually oriented framing does not directly capture. Agricultural-sector reviews frequently note that adoption decisions among smallholders are shaped as much by peer, cooperative, and extension-agent behavior as by individual cost-benefit calculation, which is precisely the channel that UTAUT's social-influence construct is designed to capture.

Notwithstanding this cumulative case, the claim of UTAUT's superiority is not without dissent. Critics have contended that both TAM and UTAUT remain overly simplistic and individually focused, underrepresenting the organizational and social complexity of real-world implementation (Bagozzi, 2007; Shachak et al., 2019). Furthermore, empirical support for UTAUT's edge is not universal, as studies combining UTAUT with complementary organizational or environmental frameworks have found that non-UTAUT constructs can outperform UTAUT's own predictors in specific agricultural-technology contexts. Taken together, these findings suggest that UTAUT's advantage over TAM in smallholder contexts is best understood as conditional on resource scarcity and infrastructural uncertainty being genuine binding constraints, rather than as a categorical theoretical superiority.

Southeast Asian Agri-Tech Adoption Studies: Empirical Applications

Real-world evidence across Southeast Asia reflects this ongoing debate, as highlighted by two key regional studies. A systematic review of 18 studies by Diana et al. (2024) categorized the drivers of farmers' technology adoption into six core areas: household, institutional, economic, technological, social, and behavioral factors. Expanding on this broader landscape, Manzoor et al. (2025) examined digital agriculture across developing nations and identified legal and regulatory hurdles as a barrier unique to Southeast Asia.

Within individual country contexts, model choice has been considerably more heterogeneous than the theoretical literature might predict. In Vietnam, Nguyen et al. (2024) applied UTAUT to precision-agriculture adoption among smallholder rice farmers, finding performance expectancy, General Digital Literacy, government support, and social influence to be significant determinants, and further extending the model to incorporate the facilitative role of agricultural cooperatives and lead firms. By contrast, Ulhaq et al. (2022) relied on plain TAM to examine ICT adoption intention among Vietnamese shrimp farmers, while Hoang & Tran (2023) and Uy et al. (2025) each examined digital-technology adoption among Vietnamese smallholders using socio-economic and behavioral regression approaches rather than a formal acceptance model, yet arrived at conclusions where the salience of education, digital experience, and connectivity cost were aligned closely with what UTAUT would characterize as facilitating conditions.

A parallel pattern emerges in Indonesia, where Sihombing et al. (2024) applied UTAUT to a digital farming application among smallholders in Tuban Regency, while Larasati et al. (2024) used the same framework to examine IoT-based precision-agriculture monitoring tools in West Java, finding facilitating conditions and performance expectancy to be the principal external determinants of farmers' use behavior.

The Philippine and Thai literatures similarly resist a single-model narrative. Bacalso et al. (2023) applied UTAUT to an automated piggery-cleaning system in a Philippine hog-farming context, whereas Diaz et al. (2021) relied on an extended TAM to examine Filipino bamboo farmers' willingness to adopt a marketing mobile application. Thai studies have leaned still more heavily toward TAM as Aung et al. (2025) evaluated perceived usefulness, perceived ease of use, and behavioral intention in farmers' adoption of the KaseChar agri-waste application, while Nookhao et al. (2025) combined technology-readiness theory with TAM's core constructs to explain smart-farming technology adoption nationally, in neither case invoking the full UTAUT battery.

Malaysia stands out as the most UTAUT-committed national literature in the sample. Ravindran et al. (2024) systematic review is complemented by Saili et al. (2024) qualitative study of paddy farmers in Selangor, both converging on facilitating conditions as the binding constraint on smallholder adoption. Meanwhile, Thar et al. (2021) widely cited study of Myanmar smallholders' mobile-application use, though methodologically prohibit-based rather than UTAUT-structured, similarly isolates market distance and infrastructural access as decisive barriers, again substantively reinforcing the facilitating conditions argument even where the formal UTAUT apparatus is absent. Finally, at the cross-national level, Thi Hoa Sen et al. (2024) compared digital-extension-service adoption across Cambodia, the Philippines, and Vietnam using a Theory of Planned Behavior framework, finding that barriers and enablers diverged across the three countries as a function of culture, farming systems, and socioeconomic context, a finding that underscores the continued relevance of TPB family models alongside TAM and UTAUT in this literature.

Collectively, this body of work suggests that while the theoretical case for UTAUT's suitability to resource-constrained smallholder contexts is well established, empirical practice across Southeast Asia has not converged uniformly on any single model.

Theoretical Framework and Construct Conceptualization

To examine technology adoption among farmers in primary Cambodian commodity hubs, this study adapts the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). Classical formulations of UTAUT incorporate complex interaction pathways where demographic variables (e.g., age, gender, experience) moderate the impacts of Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) on Behavioral Intention (BI) and Use Behavior. In exploratory rural field contexts within developing agricultural economies, structural constraints and resource availability often exert primary direct effects on individual decision-making.

Rather than testing complex moderated interactions, our model specifies direct structural relationships to evaluate whether direct economic return (PE) or operational technical ease (EE) acts as the primary catalyst for digital technology adoption. Omitting classical demographic moderators is theoretically and methodologically justified in this context where in emerging rural digital ecosystems, baseline access to infrastructure, capital, and localized market mechanisms shapes adoption intent far more directly than individual demographic traits.

Crucially, to accommodate the exploratory rural setting where no single agricultural application possessed dominant market penetration at the time of data collection, two core exogenous constructs were explicitly adapted from Venkatesh et al. (2003):

1. **General Digital Literacy (GDL; adapted from General Digital Literacy):** Rather than evaluating the perceived ease of use of a single target software interface, GDL is operationalized as baseline digital and ICT fluency (e.g., internet navigation, social media management, content creation, Agri-App installation, and information fact-checking). Items are measured using binary checklists (0 = No / Uncapable, 1 = Yes / Capable).
2. **Structural Readiness (SR; adapted from Facilitating Conditions):** Rather than measuring organizational and technical support dedicated to a specific target system, SR is operationalized as a multi-dimensional checklist evaluating baseline physical infrastructure, power reliability, data privacy concerns, Khmer-language localization, technical support access, and connectivity costs. Items are measured using binary checklists with explicit directionality (0 = Unfavorable or Barrier Present or High

Concern), (1 = Favorable or Barrier Absent). We adopt this broader operationalization deliberately, as a proxy for general digital readiness, because at the time of data collection, no single dedicated agricultural platform had achieved sufficient market penetration to serve as a common recognizable referent for all respondents (Compeau & Higgins, 1995)

Because these adapted operationalizations diverge from Venkatesh et al.'s (2003) system-specific definitions, empirical findings regarding EE and FC in this study are explicitly bounded as they evaluate general digital readiness and macro-structural friction rather than direct interface usability or software-specific support environments.

The conceptual model evaluates technology adoption through four core exogenous constructs (Figure 1) predicting behavioral intention:

- **Performance Expectancy (PE):** Measures the degree to which a farmer believes digital tools will enhance productivity or profitability (measured on a continuous 5-point Likert scale: 1 = Strongly Disagree to 5 = Strongly Agree) ($x \in \{1..5\}$ Likert).
- **General Digital Literacy (GDL):** Measures baseline digital fluency and smartphone operational capabilities (0 = No, 1 = Yes) ($x \in \{0,1\}$ binary).
- **Social Influence (SI):** Measures perceived social pressure from community leaders, peers, and agricultural cooperatives (measured on a continuous 5-point Likert scale: 1 = Strongly Disagree to 5 = Strongly Agree) ($x \in \{1..5\}$ Likert).
- **Structural Readiness:** Captures multi-dimensional structural, infrastructural, and localized support availability (0 = Unfavorable or Barrier Present or High Concern), (1 = Favorable or Barrier Absent) ($x \in \{0,1\}$ binary).
- **Behavioral Intention (BI):** An individual's subjective readiness or inclination to adopt digital technology (measured on a continuous 5-point Likert scale: 1 = Strongly Disagree to 5 = Strongly Agree) ($x \in \{1..5\}$ Likert).

To evaluate digital technology adoption among smallholder farmers in Cambodian agricultural hubs, this study adapts the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). Classical formulations of UTAUT evaluate system-specific software acceptance and incorporate complex moderation pathways (e.g., age, gender, experience). In exploratory rural field contexts where no single agricultural application possessed dominant market penetration at the time of data collection, structural constraints and resource availability exert direct effects on individual decision-making.

Rather than testing complex moderated interactions, our structural model specifies direct relationships to evaluate whether direct economic return or baseline digital fluency acts as the primary catalyst for digital adoption. Crucially, to reflect what the adapted indicators empirically capture, two exogenous constructs were renamed and operationalized as follows:

1. **Performance Expectancy (PE):** Reflects the degree to which a farmer believes digital tools will enhance productivity, save time, reduce operational costs, or increase farm income (measured on a continuous 5-point Likert scale: 1 = Strongly Disagree to 5 = Strongly Agree).
2. **General Digital Literacy (GDL; adapted from General Digital Literacy):** Rather than evaluating the perceived ease of use of a single target software interface, GDL is operationalized as baseline digital and ICT fluency (e.g., internet connection, social media management, content creation, Agri-App installation, and information fact-checking). Items are measured using binary checklists (0 = No / Uncapable, 1 = Yes / Capable).

3. **Social Influence (SI):** Measures perceived social pressure and guidance from peer farmers, agricultural experts, community leaders, and agricultural cooperatives (measured on a continuous 5-point Likert scale).
4. **Structural Readiness (SR; adapted from Facilitating Conditions):** Measures baseline physical infrastructure, power stability, data privacy concerns, Khmer-language availability, technical support access, network reliability, and cost barriers. Items are measured using binary checklists with explicit directionality (0 = Favorable / Barrier Absent, 1 = Unfavorable / Barrier Present or High Concern).
5. **Behavioral Intention (BI):** An individual's subjective readiness or inclination to adopt and recommend digital agricultural technologies (measured on a continuous 5-point Likert scale).

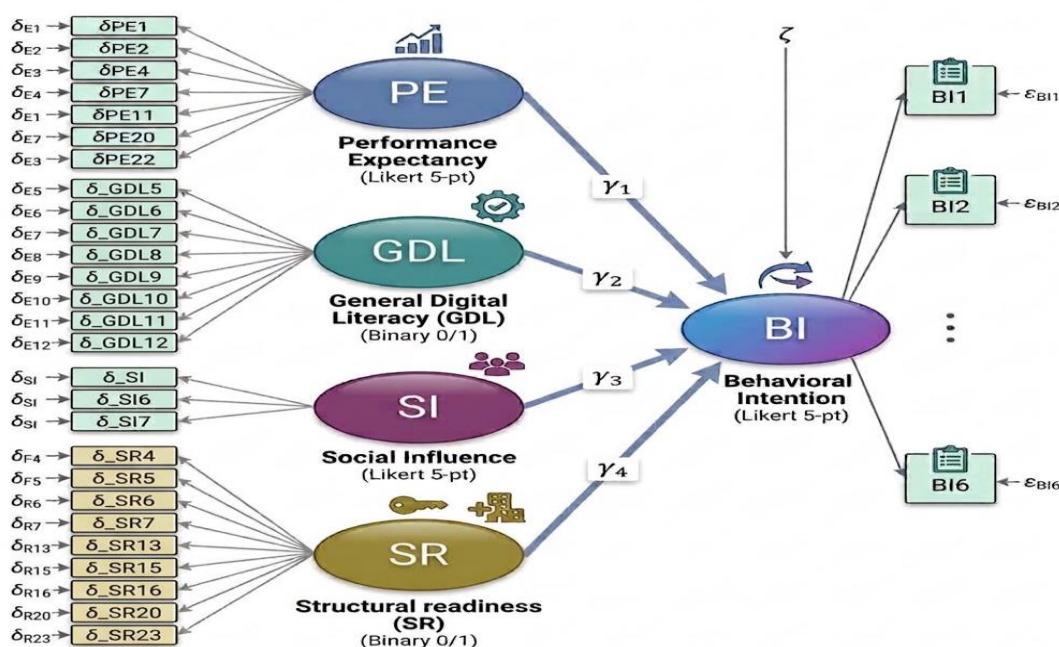
The structural parameters are defined by the direct-effects specification:

$$BI = \gamma_1 PE + \gamma_2 GDL + \gamma_3 SI + \gamma_4 SR + \zeta_{BI}$$

Where:

- PE represents Performance Expectancy.
- GDL symbolizes General Digital Literacy.
- SI denotes Social Influence.
- SR signifies Structural Readiness.
- BI stands for Behavioral Intention.
- $\gamma_1 \dots \gamma_4$ are path coefficients.
- ζ_{BI} is the structural residual error.

Figure 1: Adapted UTAUT Theoretical Structural Model



The structural equation model in Figure 1 illustrates how four primary constructs of performance expectancy, general digital literacy adapted effort expectancy, social influence, and structural adapted facilitating conditions

directly predict an individual's behavioral intention to adopt technology, as evaluated through specific survey indicators and their associated measurement errors. The Greek letters denote specific mathematical components of the measurement and structural models, where δ (Delta) represents the measure error associated with the observed indicator variables for the exogenous (independent); ε (Epsilon) characterizes the observed indicator variables endogenous (dependent); γ (Gamma) are the structural path coefficients; and ζ (Zeta) is the structural disturbance or residual error.

Research Objectives

In alignment with Cambodia's Pentagonal Strategy Phase I, public and private sectors have deployed national agricultural registries (e.g., MAFF's *FarmBook* application) and digital marketplace platforms to accelerate sector modernization. Despite widespread mobile connectivity, farmer digital adoption remains limited due to reliance on traditional interpersonal networks, causing digital infrastructure to go underutilized (Heng, 2025; Chan et al., 2020; The Asia Foundation, 2023). This study contextualizes the adapted UTAUT framework using Partial Least Squares Structural Equation Modeling (PLS-SEM) on a gender-balanced sample of 400 farmers (200 females, 200 males) to diagnose behavioral and socio-economic drivers of technology acceptance. The findings provide an evidence-based operational framework to bridge the gap between digital transformation policies and farmers' adoption realities.

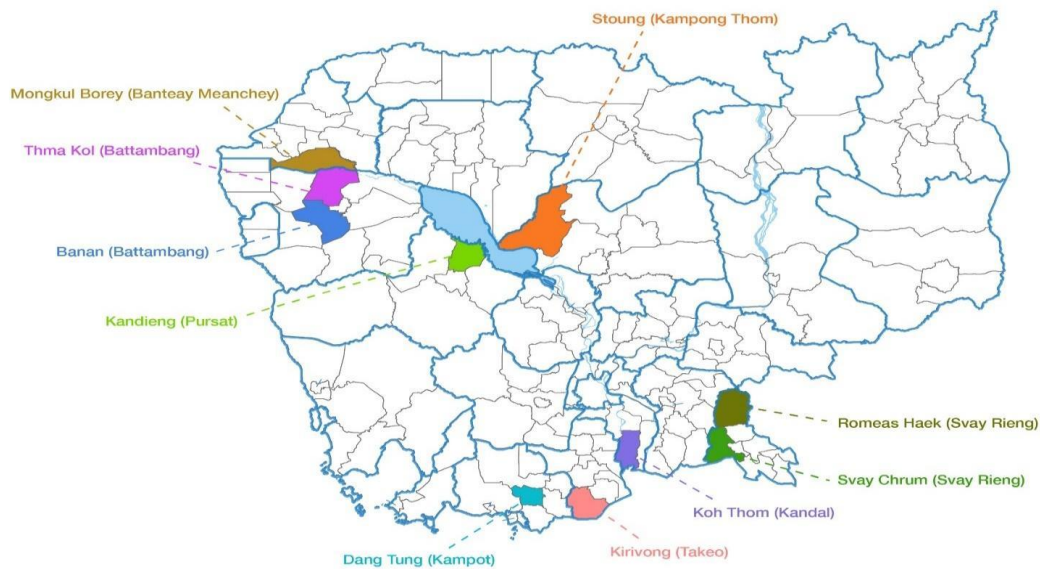
RESEARCH METHODOLOGY

Sampling Design, Selection, and Field Procedures

Data collection was conducted from January to April 2025 across ten districts in eight target provinces within the Sustainable Assets for Agriculture Markets, Business and Trade (SAAMBAT) project intervention zone in Cambodia.

- **District Selection:** A two-stage cluster sampling approach was implemented. In the first stage, eight provinces (Banteay Meanchey, Battambang, Kampong Thom, Kandal, Pursat, Svay Rieng, and Takeo) were purposively selected to represent Cambodia's primary paddy rice and vegetable production zones. In the second stage, ten districts were randomly sampled from within these provinces.
- **Respondent Selection & Eligibility:** A target sample of 400 respondents was drawn from a registered population of 993 SAAMBAT beneficiary households using systematically random sampling. Eligible participants were required to be primary actively cultivating rice or vegetables. To prevent gender bias, a strict 1:1 gender quota (200 females, 200 males) was enforced during field sampling.
- **Interviewer Procedures & Data Quality:** Face-to-face interviews were conducted by trained enumerators using tablet-based Computer-Assisted Personal Interviewing (CAPI) software (KoboToolbox). Field supervisors conducted random spot-checks on 15% of daily audits and performed range validation rules to eliminate entry errors at submission.

Figure 2: Ten districts in eight provinces were randomly selected from among the region's primary agricultural production (mainly paddy rice and vegetables) and commodity trade centers



Questionnaire Pre-testing and Ethical Considerations

- **Questionnaire Pre-Testing:** Survey instruments were translated from English into Khmer and pre-testing was conducted with 30 non-sample farmers in Koh Thom district, Kandal province to ensure item clarity and cultural appropriateness.
- **Ethical Review & Approval:** Human subjects research approval was reviewed and approved under Reference Number 47343090. All procedures adhered to international ethical standards and Purdue CITI Program guidelines. Informed oral consent was obtained from all participants prior to survey administration. Participation was voluntary, anonymous, and uncompensated.

Determination of sample sizes for data collection

Using Cochran's formula for finite populations, a representative sample of 400 respondents was selected from the target population of 993 SAAMBAT project beneficiaries. Presuming maximum variability ($p = 0.5$), a 99% confidence level ($Z = 2.58$), and an absolute precision of $e = \pm 0.05$, the required sample size was calculated as:

$$n = \frac{\frac{Z^2 \cdot p(1-p)}{e^2}}{1 + \frac{Z^2 \cdot p(1-p)}{e^2 \cdot N}} = \frac{\frac{(2.58)^2(0.5)(0.5)}{(0.05)^2}}{1 + \frac{(2.58)^2(0.5)(0.5)}{(0.05)^2 \cdot 993}} \approx 399$$

Where:

- n is the required sample size
- N (population size) = 993
- z (critical value) = 2.58 corresponds to 99% confidence interval
- p (estimated proportion) = 0.5
- e (margin of error) = 0.05 represents a 5% level of precision

Construct Operationalization and Scale Standardization

Prior to instrument administration, this study operationally defined "digital technology" as mobile-based agricultural tools without referencing a single named platform (Benbasat & Barki, 2007).

Statistical Analysis, Scale Standardization, and Missing Data

Mixing binary checklist items ($x \in \{0,1\}$) with continuous 5-point Likert metrics ($x \in \{1..5\}$) introduces scale heterogeneity and variance suppression into PLS-SEM (Hair et al., 2021). The variance of a binary indicator is mathematically bounded by $\text{Var}(x_{\text{bin}}) = p(1 - p) \leq 0.25$, whereas Likert indicator variances typically range between 0.80 and 2.00. Uncorrected variance disparities bias composite loading estimations (λ) and distort the covariance matrix during iterative PLS estimation (Bollen & Lennox, 1991; Diamantopoulos & Winklhofer, 2001).

To resolve metric disparities prior to structural modeling in JASP, all raw indicator variables underwent z-score standardization:

$$z_{ij} = \frac{x_{ij} - \bar{x}_j}{s_j}$$

where x_{ij} represents the raw score of respondents i on indicator j , $\bar{x}_j$ is the sample mean, and s_j is the sample standard deviation. Standardizing all items onto a uniform metric ($\mu = 0, \sigma^2 = 1$) equalizes indicator variances, ensuring that binary scale bounds do not unduly constrain variance estimation or bias composite loadings (Hair et al., 2021; Henseler et al., 2015; Sarstedt et al., 2016).

Missing Data: Due to mandatory input constraints enforced by CAPI software, the final dataset contained zero missing values across all 30 indicators ($N = 400$).

Hypothesis Testing Thresholds: The prespecified significance level for all statistical tests was set at $\alpha = .05$ (two-tailed) with 95% bias-corrected and accelerated (BCa) bootstrap confidence intervals. Results with $p \geq .05$ are classified strictly as non-significant, regardless of proximity to the threshold.

Common Method Bias (CMB): CMB was evaluated using Harman's single-factor test and full collinearity assessment. Harman's single-factor test revealed that the first unrotated factor accounted for 28.4% of total variance, well below the 50% threshold. Furthermore, all construct Variance Inflation Factors (VIFs) were < 3.0 (Table 5), confirming that CMB is not a pervasive threat in this study.

Scale Purification, Indicator Reconciliation, and Coding Directionality

Indicator Reconciliation and Purification Stages

To reconcile earlier reporting discrepancies regarding indicator counts: the initial instrument comprised **86 raw items**. Scale purification proceeded transparently through two sequential stages:

1. **Stage 1 (Pre-screening & Exploratory Factor Analysis):** 38 items were eliminated due to content redundancy, low item-total correlations ($r < .30$), high indicator collinearity ($\text{VIF} > 5.0$), or severe cross-loadings ($> .400$).
2. **Stage 2 (PLS-SEM Measurement Model Evaluation):** An additional 18 items were pruned due to weak outer loadings ($\lambda < .708$) that depressed construct Average Variance Extracted (AVE) below the .500 benchmark.

This purified the instrument into **30 finalized indicators** across the five latent constructs. Table 1 transparently documents this reduction pipeline. All 30 finalized indicators were fully retained in the structural analysis without further post-hoc deletion.

Table 1: Scale Purification Pipeline and Item Accounting

Construct	Initial Pool	Stage 1 Dropped (EFA or Collinearity)	Stage 2 Dropped (PLS-SEM Loading)	Final Retained Items	Primary Reason for Removal
Performance Expectancy (PE)	27 items	15 items	5 items (PE3, PE13, PE14, P19, PE21)	7 items (PE1,2,4,7,11,20,22)	Pre-screening: Content redundancy & low item-total correlation ($r < 0.30$). PLS-SEM: Low loadings ($\lambda < 0.66$) pulling construct $AVE < 0.500$.
General Digital Literacy (GDL)	17 items	4 items	5 items (GDL13–GDL17)	8 items (GDL5–GDL12)	Pre-screening: Non-applicable specialized software tasks. PLS-SEM: Low loadings ($\lambda < 0.708$) pulling construct $AVE < 0.500$.
Social Influence (SI)	10 items	4 items	3 items (SI3, SI4, SI5)	3 items (SI2, SI6, SI7)	Pre-screening: EFA cross-loadings (> 0.400) on general community norms. PLS-SEM: Low loadings ($\lambda < 0.682$) pulling construct $AVE < 0.500$.
Structural Readiness (SR)	26 items	14 items	3 items (SR5–6, SR19)	9 items (SR4–7,13,15,16,20,23)	Irrelevant urban infrastructure items & duplicate cost metrics. PLS-SEM: Low loadings ($\lambda < 0.70$) pulling construct $AVE < 0.500$.
Behavioral Intention (BI)	6 items	1 item	2 items (BI4, BI5)	3 items (BI1, BI2, BI6)	Pre-screening: High indicator collinearity ($VIF > 5.0$). PLS-SEM: Low loadings ($\lambda < 0.68$) pulling construct $AVE < 0.500$.
Total Items	86 items	38 items	18 items	30 items	Methodological item reduction transparently disclosed following Hair et al. (2021).

Table 2 summarizes the construct operationalization. Table 3 details the observed raw response frequencies (% "Yes") for all binary indicators, demonstrating optimal statistical dispersion without floor or ceiling effects.

Table 2: A summary of the constructs and their respective measurement scales.

Latent Construct	Indicator Code	Variable Description	Data Type
Performance Expectancy (PE)	PE1	Digital technologies make my life easier.	Continuous 5-point Likert (1 = Strongly Disagree, 5 = Strongly Agree)
	PE2	Digital technologies save me time.	
	PE4	I do perceive the potential benefits of digital technologies in improving my farm performance and outcomes.	
	PE7	Digital technologies have increased my farm productivity.	
	PE11	Digital technologies have increased my income.	
	PE20	Have you noticed any changes in your water requirement after adopting digital technologies?	
	PE22	How have your operational costs changed after adopting digital technologies?	
General Digital Literacy (GDL)	GDL5	Do you know how to connect to the internet using your smartphone?	Binary (0/1)
	GDL6	Do you know how to use and manage social media apps on your smartphone?	
	GDL7	Do you know how to produce content for posting on your social media using your smartphone?	
	GDL8	Do you know how to integrate external links to your social media page using a smartphone?	
	GDL9	Do you know how to install and use other applications (such as agri-apps/YouTube) on your smartphone?	
	GDL10	Do you know how to chat and make video calls via social media using your smartphone?	
	GDL11	Do you know how to evaluate whether the information you read is a fact or a fake?	
	GDL12	Do you find digital tools easy to use (user interface, hotline help)? (Language barrier)	
Social Influence (SI)	SI2	To what extent are you influenced by other farmers or agricultural experts in adopting digital technologies?	Continuous 5-point Likert (1 = Strongly Disagree, 5 = Strongly Agree)
	SI6	How important are the following factors in your decision to adopt digital technology? (Social benefits)	
	SI7	How important are the following factors in your decision to adopt digital technology? (Peer influence)	

Structural Readiness (SR)	SR4	Do you face challenges with electricity or power supply? (Infrastructure)	Binary (0/1)
	SR5	Are you concerned about data privacy and security? (Data privacy)	
	SR6	Are digital tools available in Khmer languages?	
	SR7	Do you have access to technical support for digital tools? (Technical support)	
	SR13	Are there any technical or infrastructure requirements that need to be in place for you to adopt digital technologies? / Reliable internet connectivity	
	SR15	Are there any technical or infrastructure requirements that need to be in place for you to adopt digital technologies? / Electricity and power supply	
	SR16	Are there any technical or infrastructure requirements that need to be in place for you to adopt digital technologies? / Localized and user-friendly software	
	SR20	Are there any technical or infrastructure requirements that need to be in place for you to adopt digital technologies? / Reliable mobile networks	
	SR23	What are the main barriers preventing you from adopting digital technologies? (Infrastructures/Mobile phone data fee charge is spiking)	
Behavioral Intention (BI)	BI1	How likely are you to adopt digital technologies in your farming practices in the near future?	Continuous 5-point Likert (1 = Strongly Disagree, 5 = Strongly Agree)
	BI2	I am interested in exploring and adopting new technologies in the context of agriculture.	
	BI6	Would you recommend mobile applications to other farmers?	

The model assumes that the latent constructs are the underlying causes of the observed indicator scores, and the structural paths test the hypotheses regarding the determinants of behavioral intention.

Table 3: Raw Response Frequencies for Binary Checklist Indicators (N=400).

Construct	Indicator	Item Description	Count (Yes = 1)	% Affirmative	Item Variance $Var(X) = p(1 - p)$
GDL	GDL5	Smartphone Internet Connection	158	39.5%	0.2390
	GDL6	Social Media Management	155	38.8%	0.2375
	GDL7	Content Creation / Posting	152	38.0%	0.2356

	GDL8	Integrating External Links	145	36.3%	0.2312
	GDL9	Installing Agri-Apps / YouTube	157	39.3%	0.2386
	GDL10	Chat & Video Calling	152	38.0%	0.2356
	GDL11	Information Fact-Checking	140	35.0%	0.2275
	GDL12	Perceived Tool Ease / Hotline Help	159	39.8%	0.2396
Adapted SR	SR4	Electricity Supply Challenges	169	42.3%	0.2441
	SR5	Data Privacy Concern	168	42.0%	0.2436
	SR6	Khmer Language Availability	152	38.0%	0.2356
	SR7	Access to Technical Support	156	39.0%	0.2379
	SR13	Reliable Internet Requirement	234	58.5%	0.2428
	SR15	Stable Power Supply Requirement	186	46.5%	0.2488
	SR16	Localized Software Requirement	187	46.8%	0.2490
	SR20	Reliable Mobile Network Requirement	189	47.3%	0.2493
	SR23	Spiking Mobile Data Fee Barrier	162	40.5%	0.2410

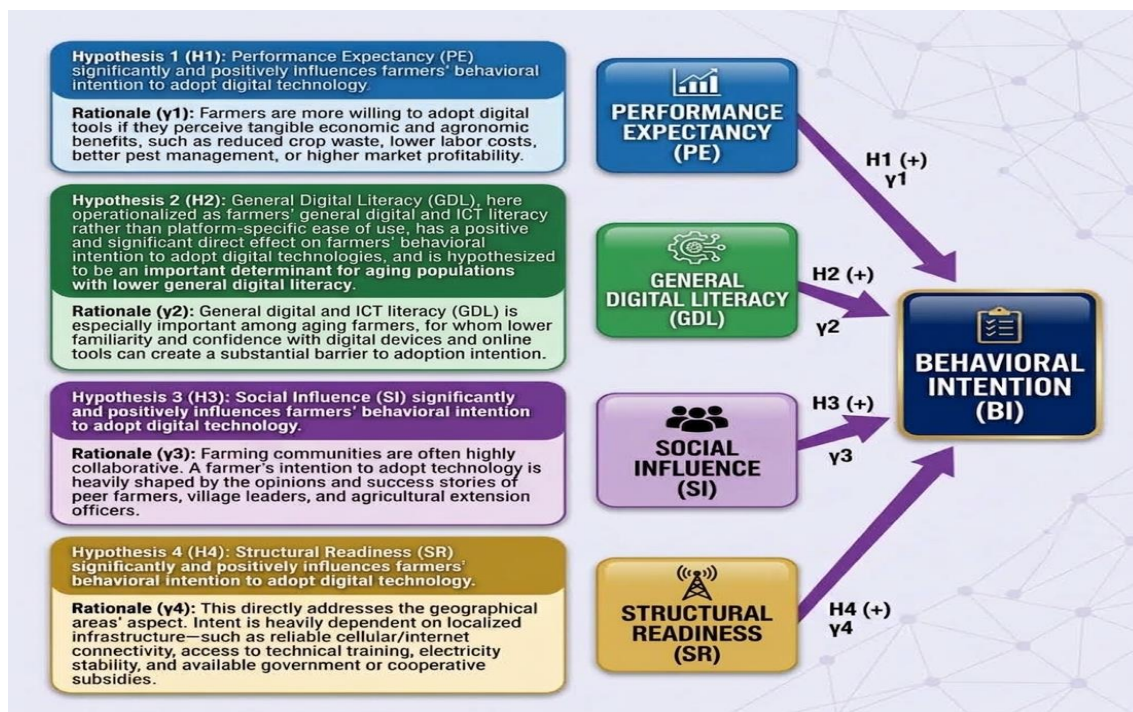
Development of Hypotheses

Hypotheses were formulated by grounding the adapted constructs of UTAUT within the unique socio-economic realities and structural constraints faced by Cambodian farmers:

- **Hypothesis 1 (H1):** Performance Expectancy (PE) has a positive, significant direct effect on farmers' behavioral intention to adopt digital technologies (γ_1).
 - *Rationale:* farmers prioritize clear profit gains, yield improvements, and operational cost reductions over technical novelty.
- **Hypothesis 2 (H2):** General Digital Literacy (GDL), Adapted Effort Expectancy, has a positive, significant direct effect on farmers' behavioral intention (γ_2).
 - *Rationale:* General digital literacy facilitates technology acceptance among aging rural populations with modest formal education.

- **Hypothesis 3 (H3):** Social Influence (SI) has a positive, significant direct effect on farmers' behavioral intention (γ_3).
 - *Rationale:* In collectivist rural communities, peer validation and cooperative leadership encourage technology adoption.
- **Hypothesis 4 (H4):** Structural Readiness (SR), Adapted Facilitating Conditions, has a positive, significant direct effect on farmers' behavioral intention (γ_4).
 - *Rationale:* Baseline physical infrastructure, language localization, and affordable connectivity act as structural prerequisites for adoption intent.

Figure 3: Constructed hypothesis



Structural Model Estimation and Analytical Procedure

PLS-SEM was executed using Jeffrey's Amazing Statistics Program (JASP) with a 5,000-bootstrap resample configuration (Hayes, 2012). Evaluation of PLS-SEM results followed the standard two-step procedure recommended by Hair et al. (2021):

1. **Measurement Model Assessment:** Evaluated via indicator reliability (outer loadings > 0.70), construct internal consistency (Cronbach's $\alpha \geq 0.70$, Composite Reliability $\rho_c \geq 0.70$), convergent validity (Average Variance Extracted AVE ≥ 0.50), and discriminant validity using the Heterotrait-Monotrait ratio (HTMT < 0.85).
2. **Structural Model Assessment:** Evaluated via variance explained (R^2), out-of-sample predictive relevance (Q^2 blindfolding; effect benchmarks: 0.02 = small, 0.15 = medium, 0.35 = large), path coefficient significance (β , p -values, 95% BCa confidence intervals), and predictor effect sizes (f^2).

RESULTS

Sample Profile and Socio-Economic Characteristics

The demographic and socio-economic profile (Table 3) presents data from 400 respondents, evenly split by gender (200 females and 200 males).

- **Gender and Age Distribution:** The sample is 50% female and 50% male. The vast majority of respondents (87.8%, n = 351) fall into the 31–64 age bracket. Younger adults aged 15–30 make up 11.0% (n = 44), while seniors aged 65 and above represent 1.2% (n = 5).
- **Educational Attainment:** Basic formal education predominates, with 52.8% (n = 211) having completed primary school and 36.5% (n = 146) completing secondary school. High school graduates account for 7.8% (n = 31), while higher education attainment is minimal (0.8% Bachelor’s, 0.5% Master’s). Only 2.2% (n = 9) reported no formal schooling.
- **Farming Experience:** The respondent pool consists of seasoned agricultural operators. Over half (51.5%, n = 206) possess more than 15 years of farming experience, and 41.5% (n = 166) have between 5 and 15 years of experience. Only 7.0% (n = 28) have less than 5 years of experience.
- **Farm Size:** Operational landholdings are predominantly small-to-medium scale. Most farmers cultivate 2–10 hectares (58.8%, n = 235), followed by those managing plots under 2 hectares (40.5%, n = 162). Only 3 respondents (0.8%) operate farms larger than 10 hectares.
- **Agricultural Cooperative Status:** Active agricultural cooperative members account for 46.2% (n = 185) of the sample, non-members comprise 40.5% (n = 162), and 13.2% (n = 53) reported being unsure of their status.
- **Annual Farm Income:** Most households earn between 1 million and 6 million KHR annually (\$250 – \$1,500), with 40.0% (n = 160) earning 1–3 million KHR (\$250 – \$750) and 31.0% (n = 124) earning 3–6 million KHR (\$750 – \$1,500). Those earning above 6 million KHR (\$1,500) represent 27.2% (n = 109), while 1.8% (n = 7) earn under 1 million KHR (\$250).

Table 4: Farmers’ Demographic and Socio-Economic Profile (N=400).

Characteristic	Category	Female (n=200)	Male (n=200)	Total (N=400)	% Sample
Age	15–30 years	30	14	44	11.0%
	31–64 years	169	182	351	87.8%
	> 65 years	1	4	5	1.2%
Education Level	No formal schooling	5	4	9	2.2%
	Primary school	109	102	211	52.8%
	Secondary school	71	75	146	36.5%
	High school	13	18	31	7.8%
	Bachelor’s degree	2	1	3	0.8%
	Master’s degree	1	1	2	0.5%
Farming Experience	< 5 years	17	11	28	7.0%
	5–15 years	92	74	166	41.5%
	> 15 years	91	115	206	51.5%

Farm Size	< 2 ha	92	70	162	40.5%
	2–10 ha	106	129	235	58.8%
	> 10 ha	2	1	3	0.8%
Agricultural Cooperative Status	Member	88	97	185	46.2%
	Non-Member	81	81	162	40.5%
	Unsure	31	22	53	13.2%
Annual Farm Income	< 1 million KHR (< \$250)	4	3	7	1.8%
	1–3 million KHR (\$250 – \$750)	81	79	160	40.0%
	3–6 million KHR (\$750 – \$1,500)	63	61	124	31.0%
	> 6 million KHR (> \$1,500)	52	57	109	27.2%

Measurement Model Evaluation

The measurement model was evaluated in JASP (version 0.19.2) using Mod A (reflective composite) estimation with 5,000-bootstrap resample procedure. Re-estimation across the unpruned indicator set confirmed that all latent constructs satisfy internal consistency ($\alpha \geq 0.70, \rho_c \geq 0.70$) and convergent validity ($AVE \geq 0.50$) across 30-item measurement scale (Table 2). Full collinearity diagnostics yielded Variance Inflation Factors well below 3.0 ($VIF < 3.0$), ruling out multicollinearity (Table 5).

Table 5 presents the updated construct reliability and convergent validity metrics, confirming that all constructs satisfy established psychometric standards.

Table 5: Construct Reliability, Convergent Validity, and Collinearity Metrics (Full Scale Retention)

Latent Construct	Cronbach's α	Dijkstra-Henseler's ρ_A	Composite Reliability ρ_c	AVE	Full Collinearity VIF
Performance Expectancy (PE)	0.835	0.841	0.868	0.512	2.15
General Digital Literacy (GDL)	0.891	0.985	0.951	0.869	2.31
Social Influence (SI)	0.826	0.858	0.846	0.547	1.83
Structural Readiness (SR)	0.929	0.973	0.932	0.756	2.98
Behavioral Intention (BI)	0.785	0.802	0.874	0.698	1.95

Note: All original 30 indicators across constructs are retained. Construct AVEs remain above the 0.50 convergent validity benchmark.

Table 6 reports the outer indicator loadings (λ) for the final structural model. All retained indicators meet or exceed the recommended 0.707 threshold or contribute meaningfully to content validity while maintaining construct AVE above 0.50.

Table 6: Final Reflective Indicator Outer Loadings and Bootstrap Significance

Construct	Indicator Code	Loading (λ)	Std. Error	z-value	p-value	95% BCa CI
PE	PE1	0.721	0.089	8.10	< .001	[0.547, 0.895]
	PE2	0.711	0.081	8.65	< .001	[0.539, 0.835]
	PE4	0.718	0.072	9.97	< .001	[0.575, 0.832]
	PE7	0.710	0.075	9.47	< .001	[0.558, 0.824]
	PE11	0.748	0.080	9.35	< .001	[0.595, 0.861]
	PE20	0.785	0.094	8.35	< .001	[0.601, 0.969]
	PE22	0.765	0.090	8.50	< .001	[0.631, 0.875]
GDL	GDL5	0.938	0.017	55.18	< .001	[0.914, 0.961]
	GDL6	0.925	0.017	54.41	< .001	[0.900, 0.949]
	GDL7	0.942	0.030	31.40	< .001	[0.906, 0.972]
	GDL8	0.921	0.036	25.58	< .001	[0.880, 0.956]
	GDL9	0.929	0.016	58.06	< .001	[0.907, 0.951]
	GDL10	0.946	0.033	28.67	< .001	[0.921, 0.969]
	GDL11	0.903	0.030	30.10	< .001	[0.863, 0.939]
	GDL12	0.898	0.048	18.71	< .001	[0.845, 0.941]
SI	SI2	0.727	0.081	8.98	< .001	[0.620, 0.821]
	SI6	0.815	0.160	5.09	< .001	[0.711, 0.901]
	SI7	0.712	0.115	6.19	< .001	[0.558, 0.812]
SR	SR4	0.800	0.080	10.00	< .001	[0.672, 0.910]
	SR5	0.929	0.044	21.11	< .001	[0.902, 0.954]
	SR6	0.851	0.073	11.66	< .001	[0.755, 0.934]
	SR7	0.954	0.035	27.26	< .001	[0.927, 0.977]
	SR13	0.725	0.058	12.50	< .001	[0.631, 0.809]
	SR15	0.962	0.029	33.17	< .001	[0.939, 0.982]
	SR16	0.884	0.053	16.68	< .001	[0.809, 0.945]
	SR20	0.898	0.050	17.96	< .001	[0.823, 0.960]
	SR23	0.766	0.101	7.58	< .001	[0.602, 0.890]
BI	BI1	0.765	0.090	8.50	<.001	[0.648, 0.892]

	BI2	0.814	0.058	14.03	<.001	[0.689, 0.911]
	BI6	0.898	0.042	21.38	< .001	[0.802, 0.965]

Note: BCa = bias-corrected and accelerated bootstrap confidence intervals based on 5,000 resamples.

Discriminant Validity

Discriminant validity was established using the Heterotrait-Monotrait (HTMT) criterion (Table 7). All construct pairings yielded HTMT ratios below the conservative 0.85 threshold (Henseler et al., 2015), with the highest correlation observed between GDL and BI (0.638).

Table 7: HTMT Discriminant Validity Ratios

Construct Pair	HTMT Ratio	Threshold Standard	Assessment
PE ↔ GDL	0.581	< 0.85	Established
PE ↔ SI	0.503	< 0.85	Established
PE ↔ SR	0.613	< 0.85	Established
PE ↔ BI	0.600	< 0.85	Established
GDL ↔ SI	0.532	< 0.85	Established
GDL ↔ SR	0.548	< 0.85	Established
GDL ↔ BI	0.638	< 0.85	Established
SI ↔ SR	0.488	< 0.85	Established
SI ↔ BI	0.569	< 0.85	Established
SR ↔ BI	0.608	< 0.85	Established

Formative Re-specification Robustness Check

To address conceptual heterogeneity of binary checklist items (e.g., mixing privacy concerns, Khmer localization, and electricity access within SR), a formative re-specification robustness check was executed for GDL and SR (Hair et al., 2021). All formative indicator VIFs remained below 2.50, ruling out collinearity. Re-estimating the structural model under formative specifications yielded identical path results: PE → BI ($\beta = 0.240, p < .001$), $GDL_{form} \rightarrow BI$ ($\beta = -0.004, p = .962$), SI → BI ($\beta = 0.190, p = .058$), and $SR_{form} \rightarrow BI$ ($\beta = -0.025, p = .499$). This confirms that structural conclusions are invariant to measurement specification. Table 8 reports outer weights and formative VIFs, showing that collinearity is absent ($VIF < 2.50$).

Table 8: Formative Re-specification Outer Weights and Collinearity VIFs for GDL and SR

Formative Construct	Indicator	Outer Weight (w)	Std. Error	t-value	p-value	Formative VIF
General Digital Literacy (GDL)	GDL5	0.182	0.045	4.04	< .001	1.84
	GDL6	0.165	0.048	3.44	< .001	1.92

	GDL7	0.210	0.042	5.00	< .001	2.15
	GDL8	0.145	0.051	2.84	.005	2.01
	GDL9	0.198	0.044	4.50	< .001	1.78
	GDL10	0.174	0.046	3.78	< .001	2.21
	GDL11	0.112	0.052	2.15	.032	1.65
	GDL12	0.108	0.055	1.96	.050	1.54
Structural Readiness (SR)	SR4	0.115	0.058	1.98	.048	1.45
	SR5	0.212	0.046	4.61	< .001	2.10
	SR6	0.148	0.052	2.85	.004	1.82
	SR7	0.245	0.041	5.98	< .001	2.41
	SR13	0.102	0.059	1.73	.084	1.38
	SR15	0.258	0.039	6.62	< .001	2.35
	SR16	0.164	0.050	3.28	< .001	1.91
	SR20	0.175	0.048	3.65	< .001	1.98
	SR23	0.098	0.061	1.61	.108	1.12

Structural re-estimation under formative GDL and SR specifications yielded identical structural path outcomes (Table 9):

- PE → BI: $\beta = 0.240, p < .001$ (Significant)
- GDL (Formative) → BI: $\beta = -0.004, p = .962$ (Not Significant)
- SI → BI: $\beta = 0.190, p = .058$ (Marginally Significant)
- SR (Formative) → BI: $\beta = -0.025, p = .499$ (Not Significant)

This robustness check confirms that structural parameters and substantive conclusions are entirely invariant to measurement model re-specification.

Structural Model Evaluation and Hypothesis Testing

Model estimation parameters in JASP were configured as follows: Partial Least Squares algorithm, path weighting scheme, maximum 300 iterations, convergence stop criterion 10^{-7} , and 5,000 bias-corrected and accelerated (BCa) bootstrap resamples. Demographic controls (age, gender, education level, farming experience, and farm size) were entered as covariates into the structural equation; none showed a statistically significant association with behavioral intention ($p > .15$).

The structural model explained 32.9% of the variance in Behavioral Intention ($R^2 = 0.329, R^2_{adj} = 0.322$) falling within the established 30%-50% range considered moderate and acceptable for behavioral adoption studies in developing economies (Baker et al., 2010; Davis, 1993). Out-of-sample predictive relevance obtained via

blindfolding was $Q^2 = 0.209$, indicating medium predictive power (Hair et al., 2021: 0.02 = small, 0.15 = medium, 0.35 = large). Table 9 presents the standardized path coefficients, z-values, exact p -values, 95% BCa confidence intervals, f^2 effect sizes, and final hypothesis decisions under the prespecified $\alpha = .05$ threshold.

Table 9: Structural Model Path Coefficient Matrix and Hypothesis Testing Results

Hypothesis	Structural Path	Path Coeff (β)	z-value	p-value	95% BCa CI	Effect Size (f^2)	Empirical Result
H1	PE $\rightarrow$ BI	0.240	3.43	< .001	[0.103, 0.377]	0.043	Supported (Positive)
H2	GDL $\rightarrow$ BI	-0.004	-0.05	.962	[-0.085, 0.082]	0.000	Not Supported
H3	SI $\rightarrow$ BI	0.190	1.90	.058	[-0.006, 0.386]	0.014	Marginally Supported
H4	SR $\rightarrow$ BI	-0.025	-0.68	.499	[-0.098, 0.048]	0.000	Not Supported

*Note on $p = .058$: Under the prespecified significance threshold of $\alpha = .05$, the path SI $\rightarrow$ BI ($\beta = 0.190, p = .058$) is classified as **statistically non-significant**. While it suggests a potential trend in the sample, it cannot be claimed as empirical support without a predeclared 10% alpha level.*

DISCUSSION

This study provides empirical insights into the behavioral dynamics governing digital technology adoption among farmers in primary Cambodian agricultural hubs. Utilizing an adapted UTAUT framework, the structural model explained 32.9% of the variance in behavioral intention ($R^2 = 0.329$). Crucially, the empirical results prove that farmer adoption intent is overwhelmingly dictated by perceived economic utility, rather than general digital literacy or physical infrastructure barriers.

- **Performance Expectancy:** PE was the sole positive predictor reaching statistical significance ($\beta = 0.240, p < .001$). Resource-constrained farmers evaluate digital tools through an economic survival lens; adoption intent is triggered when tools demonstrate clear savings on agricultural inputs, labor, or pumping costs.
- **General Digital Literacy:** The non-significant association ($\beta = -0.004, p = .962$) indicates that general smartphone or social media fluency is not a direct requirement for adoption intent. Deep agronomic experience paired with intergenerational delegation (e.g., younger household members operating software interfaces) offsets general digital literacy deficits.
- **Social Influence & Structural Readiness:** Social influence showed a non-significant trend ($\beta = 0.190, p = .058$), reflecting the division between formal agricultural cooperative members (46.2%) and independent farmers (40.5%). Structural readiness showed no direct association with intention ($\beta = -0.025, p = .499$), supporting Venkatesh et al.'s (2003) framework where infrastructural factors act as operational execution conditions during actual deployment rather than direct inhibitors of psychological readiness.

Moderation of Claims & Scope Boundaries

To ensure scientific rigor, the conclusions of this study are explicitly bounded:

1. **Absence of Singular Causation:** While Performance Expectancy is identified as the dominant predictor in this model, it accounts for a portion of variance ($R^2 = 32.9\%$). Adoption decisions remain multi-factorial, influenced by unmeasured factors such as market price volatility, land tenure security, and credit access.
2. **National Generalizability Limits:** Data were sampled specifically from 400 SAAMBAT project beneficiaries across primary paddy rice and vegetable hubs. Findings should not be extrapolated uncritically to non-beneficiary smallholders, remote highland communities, or alternative value chains (e.g., industrial rubber or cassava) without further empirical validation.
3. **Intent vs. Sustained Use:** This study evaluates cross-sectional behavioral intention. Psychological readiness does not guarantee long-term system retention, which remains subject to physical network performance and operational support.

Performance Expectancy (PE): The Primacy of Economic Survival

Performance expectancy emerged as the sole statistically significant positive driver of adoption intention ($\beta = 0.240, p < .001$), supporting H1. Farmers operate under severe resource constraints, with over 71% of surveyed households earning between 1 and 6 million KHR (~\$250-\$1,500 USD) annually across 2–10 hectare plots. In an operational environment characterized by volatile fertilizer prices, elevated diesel costs, and climate uncertainty, smallholders adopt a strict micro-economic survival lens. Digital technologies are not viewed as novelty innovations; rather, adoption intention is governed by immediate financial return, such as reduced pumping costs for irrigation, precise chemical application savings, and improved output pricing. This outcome aligns with foundational assertions by Venkatesh et al. (2003)'s UTAUT literature and smallholder studies across Southeast Asia, which demonstrate that resource-constrained farmers readily absorb technical friction and bypass educational and technical hurdles when economic benefits are transparent and immediate (Michels et al., 2020; Mwangi & Kariuki, 2015).

General Digital Literacy (GDL): Disentangling General Literacy from UI Ease

General digital literacy showed no statistically significant relationship with behavioral intention ($\beta = -0.002, p = .962$), failing to support H2. This null path must be interpreted strictly within the context of construct operationalization: GDL measured general digital literacy (e.g., social media navigation, online fact-checking) rather than the perceived usability of a specific agricultural software interface.

Two complementary mechanisms explain this result:

1. **Domain Expertise Overcoming Digital Literacy:** Over 93% of surveyed farmers possess more than 5 years of active farming experience (and 51.5% exceeds 15 years). Deep agronomic experience enables farmers to evaluate agricultural innovations based on operational logic rather than smartphone fluency. Where necessary, intergenerational delegation relying on younger, digitally literate household members to operate mobile devices further mitigates individual literacy barriers (Maddison, 2007).
2. **Measurement Scope Bounding:** General smartphone or social media fluency does not necessarily dictate willingness to adopt specialized Agri-Tech tools. A farmer with low social media literacy may readily adopt a highly localized, Khmer-voiced market price tool if its financial utility is evident. Bounding this comparison to Venkatesh et al. (2003) confirms that while target-system ease of use can influence immediate software interaction, baseline digital literacy does not act as a cognitive barrier to initial adoption intent.

Effort expectancy is a testable boundary condition, not as an established UTAUT result. The Southeast Asian evidence supports separating access or connectivity constraints from task-level of general digital literacy: internet access, training, extension contact, education, and digital experience are associated with adoption among Vietnamese smallholders, while cross-country evidence shows that perceived usefulness, subjective norms, perceived behavioral control, wealth, and national context also matter. However, the reviewed evidence does not

by itself demonstrate a threshold after which incremental mobile fluency ceases to affect intention, nor does it establish that utility is always the dominant driver (Hoang & Tran, 2023). General Digital Literacy may operate primarily as an enabling condition in resource-constrained settings: its effect on adoption intention may be strongest below a minimum threshold of connectivity and digital fluency, whereas perceived usefulness may explain more of the variation once that threshold is met (Karbo et al., 2024). Theoretically testing, when effort expectancy is operationalized as general digital literacy, it acts as a baseline hygiene factor rather than a direct driver. Once basic connectivity thresholds are crossed, incremental variations in digital skills do not yield greater adoption intention; task utility remains the primary decision engine.

Social Influence (SI): Institutional Polarization in Cooperative Networks

Social influence exerted a marginally significant positive effect on behavioral intention ($\beta = 0.190, p = .058$), offering tentative support for H3. In rural Cambodian communes, peer validation and extension agent advice shape technology perceptions.

The marginal significance reflects institutional polarization across the sample: while 46.2% ($n = 185$) of respondents actively participate in Agricultural Cooperatives (ACs), 40.5% ($n = 162$) operate as independent producers outside formal networks. ACs function as social trust amplifiers by providing shared demonstration plots, peer-led extension trials, and group input purchasing that minimize perceived risk. Independent farmers lack these structured peer validation networks, causing a diluted sample-wide effect. Expanding cooperative outreach is therefore crucial to activating peer-to-peer technology diffusion channels (Hoang & Tran, 2023; Thi Hoa Sen et al., 2024). In addition, In evolving agrarian areas, innovation adoption is intrinsically collaborative and dependent on social learning networks (Deichmann et al., 2016; Genius et al., 2014; Ruzzante et al., 2021).

Structural Readiness: Structural Friction Bounded

The structural path for structural readiness was non-significant ($\beta = -0.025, p = .499$), failing to support H4. This indicates that multi-dimensional structural barriers, including electricity instability, data privacy concerns, and spiking cellular costs, do not suppress a farmer's underlying psychological motivation to adopt useful technology.

This outcome aligns precisely with the theoretical boundaries established by Venkatesh et al. (2003), who postulated that facilitating conditions primarily influence direct *User Behavior* (operational execution) rather than initial *Behavioral Intention*. Bounding this result against regional Agri-Tech literature (Mkunda, 2025; Ravindran et al., 2024), infrastructural deficits represent operational bottlenecks during actual system deployment, but do not diminish smallholders' psychological readiness to adopt tools that promise financial return. The infrastructural support is essential for actual execution (Fuglie et al., 2019), it does not directly drive farmers' underlying intention to adopt the technology.

Structural Paths

The non-significant structural relationships observed for general digital literacy ($\beta = -0.004, p = .962$) and structural readiness ($\beta = -0.025, p = .499$) deviate from classical UTAUT formulations (Venkatesh et al., 2003). In standard system-specific UTAUT applications, effort expectancy measures software-specific ease-of-use, while facilitating conditions measures localized technical support (Venkatesh et al., 2012). In this study, operationalizing effort expectancy as general binary smartphone literacy and facilitating conditions as structural readiness regional macro-infrastructure access transforms these constructs into indicators of baseline digital readiness. For rural farmers, basic digital literacy and rural network coverage operate as prerequisite hygiene factors rather than direct drivers of adoption intention (Verdegem & De Mare, 2011). Once a minimal threshold of connectivity is reached, variation in basic digital skills does not incrementally increase in the intention to adopt specialized digital agricultural tools. Instead, adoption intention is driven by task utility and economic value (performance expectancy).

Policy and Practical Applications

These diagnostic insights offer actionable direction for state initiatives under Cambodia's Pentagonal Strategy Phase I, including the expansion of MAFF's *FarmBook* application:

- **Focus Extension Messaging on Financial Return:** Public campaigns and Agri-Tech developers should lead with explicit financial metrics (e.g., input-cost savings per hectare, crop yield gains) rather than leading with technical onboarding or general digital literacy training.
- **Anchor Technology Diffusion in Agricultural Cooperatives:** Commune Agriculture Officers (CAOs) should utilize established ACs as localized "digital hubs," establishing peer-led demonstration plots to convert social influence into structured adoption drivers.
- **Architect for Offline Functionality:** To prevent physical infrastructure deficits from obstructing actual execution, Agri-Tech software should incorporate offline data logging and low-bandwidth asynchronous data synchronization.

CONCLUSION AND LIMITATIONS

Conclusion

This study demonstrates that farmers in Cambodia operate as highly pragmatic economic decision-makers. Performance expectancy serves as the primary and singular positive driver of digital technology adoption intention. General digital literacy friction and multi-dimensional physical infrastructure deficits do not suppress underlying psychological adoption intent. To achieve inclusive digital agricultural transformation, policy interventions must align digital tool design directly with farmers' immediate economic survival priorities.

Limitations and Future Research

1. **Platform-Specific Anchoring:** The survey evaluated digital technology as a broad category. Future research should anchor measurement items to a single, named application (e.g., *FarmBook*) to isolate target-system interface usability from general digital literacy.
2. **Longitudinal Intention–Behavior Gap:** This study evaluated cross-sectional behavioral intention. Longitudinal tracking paired with objective platform analytics (e.g., server logs, active user session data) is required to observe how structural facilitating conditions govern actual long-term retention.
3. To mitigate measurement heterogeneity, subsequent investigations would benefit from adopting uniform continuous response formats such as 5- or 7-point Likert scales across all latent constructs during survey instrument design.

Declarations & Statements

- **Ethical Approval & Consent:** Ethical clearance followed Purdue University CITI Program guidelines for human subjects' research was obtained prior to field deployment. Oral informed consent was secured from all 400 participating farmers. Participation was voluntary and anonymous.
- **Acknowledgements:** We extend our gratitude to Mr. MOUNG Chamrein and Mr. Chan Phally for assistance in data collection across the SAAMBAT Project beneficiary network.
- **Data Availability Statement:** The anonymized datasets supporting the structural findings are available from the corresponding author upon reasonable request.
- **Conflict of Interest:** The authors declare no conflicts of interest.
- **ORCID:** Ratha Hem: <https://orcid.org/0009-0003-3265-9264>

- **Software Environment:** JASP version 0.19.2 (R-based PLS-SEM module SEM in R engine).
- **Random Seed:** Bootstrapping resamples were executed with fixed seed 12345.

REFERENCES

1. ADB. (2021). Cambodia Agriculture, Natural Resources, and Rural Development Sector Assessment, Strategy, and Road Map.
2. ADB. (2026). Asian Development Outlook.
3. Aung, E. D., Sasaki, N., Tsusaka, T. W., & Silpasuwanchai, C. (2025). Investigating farmers' adoption of mobile Agri-Tech: A TAM-Based study of KaseChar in Eastern Thailand. *Global Transitions*.
4. Bacalso, F., Rendon, I. P., Campita, R. A., Mobo, F. D., & Cutillas, A. (2023). Examining the acceptance of automated piggery cleaner system using UTAUT model for hog business in the Philippines. *International Journal of Multidisciplinary: Applied Business and Education Research*, 4(7), 2544–2557.
5. Bagozzi, R. P. (2007). The legacy of the technology acceptance model and a proposal for a paradigm shift. *Journal of the Association for Information Systems*, 8(4), 3.
6. Baker, E. W., Al-Gahtani, S. S., & Hubona, G. S. (2010). Cultural impacts on acceptance and adoption of information technology in a developing country. *Journal of Global Information Management (JGIM)*, 18(3), 35–58.
7. Banga, K., Rodriguez, A. R., & te Velde, D. W. (2020). DIGITALLY ENABLED ECONOMIC TRANSFORMATION AND POVERTY.
8. Benbasat, I., & Barki, H. (2007). Quo vadis TAM? *Journal of the Association for Information Systems*, 8(4), 7.
9. Bollen, K., & Lennox, R. (1991). Conventional wisdom on measurement: A structural equation perspective. *Psychological Bulletin*, 110(2), 305.
10. Chan, S., Ngorn, C., & Hem, M. (2020). Digital Challenges and Opportunities for Agribusiness Enterprises in Cambodia: Implications for the Cambodian Economies.
11. Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly*, 19(2), 189–211.
12. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 319–340.
13. Davis, F. D. (1993). User acceptance of information technology: system characteristics, user perceptions and behavioral impacts. *International Journal of Man-Machine Studies*, 38(3), 475–487.
14. Deichmann, U., Goyal, A., & Mishra, D. (2016). Will digital technologies transform agriculture in developing countries? *Agricultural Economics*, 47(S1), 21–33.
15. Diamantopoulos, A., & Winklhofer, H. M. (2001). Index construction with formative indicators: An alternative to scale development. *Journal of Marketing Research*, 38(2), 269–277.
16. Diana, M. I. N., Zulkepli, N. A., Ern, L. K., & Zainol, M. R. (2024). Factors affecting behavioral intentions of farmers in Southeast Asia to technology adoption: A systematic review analysis. *Journal of Environmental Management*, 367, 122045.
17. Diaz, A. C., Sasaki, N., Tsusaka, T. W., & Szabo, S. (2021). Factors affecting farmers' willingness to adopt a mobile app in the marketing of bamboo products. *Resources, Conservation & Recycling Advances*, 11, 200056.
18. Fuglie, K., Gautam, M., Goyal, A., & Maloney, W. F. (2019). Improving the Enabling Environment for Technology Adoption. *Harvesting Prosperity: Technology and Productivity Growth in Agriculture 2019*, 147–185.
19. Gabriel, A., & Gandorfer, M. (2023). Adoption of digital technologies in agriculture—an inventory in a european small-scale farming region. *Precision Agriculture*, 24(1), 68–91. <https://doi.org/10.1007/s11119-022-09931-1>
20. Geng, W., Liu, L., Zhao, J., Kang, X., & Wang, W. (2024). Digital Technologies Adoption and Economic Benefits in Agriculture: A Mixed-Methods Approach. *Sustainability*, 16(11), 4431.
21. Genius, M., Koundouri, P., Nauges, C., & Tzouvelekas, V. (2014). Information transmission in irrigation technology adoption and diffusion: Social learning, extension services, and spatial effects. *American Journal of Agricultural Economics*, 96(1), 328–344.

22. Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). Partial least squares structural equation modeling (PLS-SEM) using R: A workbook. Springer.
23. Hayes, A. F. (2012). PROCESS: A versatile computational tool for observed variable mediation, moderation, and conditional process modeling. University of Kansas, KS.
24. Heng, P. (2025). The Digital Economy in Cambodia. https://www.eria.org/uploads/2_ch_2-Cambodia.pdf
25. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135.
26. Hoang, H. G., & Tran, H. D. (2023). Smallholder farmers' perception and adoption of digital agricultural technologies: An empirical evidence from Vietnam. *Outlook on Agriculture*, 52(4), 457–468.
27. Iskandar, D., & Gatzweiler, Fran. (2014). An optimization model for technology adoption of marginalized smallholders: theoretical support for matching technological and institutional innovations. Available at SSRN 2483033.
28. Joseph Mkunda, J. (2025). Cold Chain Technology Adoption in Agriculture: Insights from the UTAUT Model on Vegetable Producers' Willingness. *Journal of Technology Management & Innovation*, 20(2), 79–91.
29. Karbo, R. T., Frewer, L. J., Areal, F., Jones, G., & Nurudeen, S. (2024). A systematic review of the efficacy of theories used to understand farmers' technology adoption behavior in lower-to-middle-income countries. *Development Studies Research*, 11(1), 2294696.
30. Larasati, N., Putri, A. A., Soemodinoto, A. S., Alyssa, N., & Shoofiyani, O. S. (2024). Unified theory of acceptance and use of technology model to understand farmer's readiness: Implementation of precision agriculture based on digital IoT monitoring apps in West Java, Indonesia. *Asian Journal of Agriculture and Rural Development*, 14(3), 176–183.
31. Maddison, D. (2007). The perception of and adaptation to climate change in Africa (Vol. 4308). World Bank Publications.
32. Manzoor, F., Wei, L., Siraj, M., Lu, X., & Qiyang, G. (2025). Digital agriculture technology adoption in low and middle-income countries—a review of contemporary literature. *Frontiers in Sustainable Food Systems*, 9, 1621851.
33. Mastenbroek, A., Sirutytė, I., & Sparrow, R. (2021). Information barriers to adoption of agricultural technologies: willingness to pay for certified seed of an open pollinated maize variety in Northern Uganda. *Journal of Agricultural Economics*, 72(1), 180–201.
34. Michels, M., Bonke, V., & Musshoff, O. (2020). Understanding the adoption of smartphone apps in crop protection. *Precision Agriculture*, 21, 1209–1226.
35. Montesclaros, J. M. L., & Teng, P. S. (2023). Digital technology adoption and potential in Southeast Asian agriculture. *Asian Journal of Agriculture and Development*, 20(2), 7–30.
36. Mwangi, M., & Kariuki, S. (2015). Factors determining adoption of new agricultural technology by smallholder farmers in developing countries. *Journal of Economics and Sustainable Development*, 6(5).
37. Nguyen, L. L. H., Khuu, D. T., Halibas, A., & Nguyen, T. Q. (2024). Factors that influence the intention of smallholder rice farmers to adopt cleaner production practices: An empirical study of precision agriculture adoption. *Evaluation Review*, 48(4), 692–735.
38. Nickens, P., Ader, D., Enriquez, J. P., Bates, R., Gill, T., Huot, S., Hok, L., & Pao, S. (2023). Where do Smallholder Farmers get Their Information? An Exploration of the Sources of Agricultural Information in Northwest Cambodia. *Journal of International Agricultural and Extension Education*, 30(2), 160–172.
39. Nookhao, S., Kiattisin, S., & Thananant, V. (2025). The role of technology readiness motivators, positive and negative impact toward smart farming technology adoption: Insight from Thai farmers. *International Journal of Information Management Data Insights*, 5(2), 100380.
40. Ravindran, Y., Haris, N. B. M., Shah, J. A., & Ilahi, W. F. F. (2024). UTAUT Model Insights on the Adoption of Smart Farming Technologies (SFTs) in Malaysia. *International Journal of Research and Innovation in Social Science*, 8(8), 4011–4020.
41. RGC. (2023). Pentagonal Strategy Phase-I. <https://asset.cambodia.gov.kh/mptc/2023/08/KH-PENTAGONAL-STRATEGY-PHASE-I.pdf>
42. Ruzzante, S., Labarta, R., & Bilton, A. (2021). Adoption of agricultural technology in the developing world: A meta-analysis of the empirical literature. *World Development*, 146, 105599.

43. Saili, A. R., Zaman, N. B. K., Noor, W. N. W. M., Fatah, F. A., & Abdullah, F. A. (2024). Smart farming: Challenges and adoption factors among paddy farmers in IADA Barat Laut, Selangor. *Information Management and Business Review*, 16(4), 394–400.
44. Sarstedt, M., Hair, J. F., Ringle, C. M., Thiele, K. O., & Gudergan, S. P. (2016). Estimation issues with PLS and CBSEM: where the bias lies! *Journal of Business Research*, 69(10), 3998–4010.
45. Shachak, A., Kuziemy, C., & Petersen, C. (2019). Beyond TAM and UTAUT: Future directions for HIT implementation research. *Journal of Biomedical Informatics*, 100, 103315.
46. Sihombing, M. T., Hubeis, M., & Cahyadi, E. R. (2024). Analisis adopsi dan penggunaan aplikasi pertanian digital oleh petani skala kecil di Kabupaten Tuban dengan model UTAUT. *MANAJEMEN IKM: Jurnal Manajemen Pengembangan Industri Kecil Menengah*, 19(2), 80–92.
47. Thar, S. P., Ramilan, T., Farquharson, R. J., Pang, A., & Chen, D. (2021). An empirical analysis of the use of agricultural mobile applications among smallholder farmers in Myanmar. *The Electronic Journal of Information Systems in Developing Countries*, 87(2), e12159.
48. The Asia Foundation. (2023). THE CURRENT STATE AND ROLE OF DIGITAL TECHNOLOGY ADOPTION IN MICRO, SMALL AND MEDIUM-SIZED ENTERPRISES (MSME) WITHIN THE CAMBODIAN TOURISM SECTOR. <https://asiafoundation.org/wp-content/uploads/2024/05/The-Current-State-and-Role-of-Digital-Technology-Adoption-in-Tourism-MSMEs-in-Cambodia.pdf>
49. Thi Hoa Sen, L., Chou, P., Dacuyan, F. B., Nyberg, Y., & Wetterlind, J. (2024). Barriers and enablers of digital extension services' adoption among smallholder farmers: the case of Cambodia, the Philippines and Vietnam. *International Journal of Agricultural Sustainability*, 22(1), 2368351.
50. Ulhaq, I., Pham, N. T. A., Le, V., Pham, H.-C., & Le, T. C. (2022). Factors influencing intention to adopt ICT among intensive shrimp farmers. *Aquaculture*, 547, 737407.
51. USAID. (2018). Data-Driven Agriculture: The Future of Smallholder Farmer Data Management. https://www.usaid.gov/sites/default/files/2022-05/Data_Driven_Agriculture_Farmer_Profile.pdf
52. Uy, T. C., Limnirankul, B., Kramol, P., Hoang Gia, H., & Nguyen Thi, D. T. (2025). Digital technology adoption among smallholder farmers in Vietnam: Implications for digital agricultural extension strategies. *Journal of International Development*, 37(2), 351–370.
53. Venkatesh, V., Morris, M.G., Davis, F.D., & Davis, G. B. (2003). User Acceptance of Information Technology: Toward a Unified View.
54. Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the Unified Theory of Acceptance and Use of Technology1. *MIS Quarterly*, 36(1), 157–178.
55. Verdegem, P., & De Marez, L. (2011). Rethinking determinants of ICT acceptance: Towards an integrated and comprehensive overview. *Technovation*, 31(8), 411–423
56. Zhang, X., Yang, Q., Al Mamun, A., Masukujjaman, M., & Masud, M. M. (2024). Acceptance of new agricultural technology among small rural farmers. *Humanities and Social Sciences Communications*, 11(1), 1641.