

Analysis of B2B Agricultural E-Commerce Model Based on Institutional Buyer Adoption Using the UTAUT Framework

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Abstract

This study analyzes institutional buyers' need for and intention to adopt B2B agricultural e-commerce in Manado City and the factors shaping that intention, using UTAUT extended with Trust. A quantitative explanatory approach was applied to institutional buyers across sectors including restaurants/cafes, hotels, hospitals, catering, modern markets and MBG kitchens; 115 of 120 responses were retained after screening for careless responding and analyzed by PLS-SEM in SmartPLS 4, with nine hypotheses tested via 5,000-subsample bootstrapping. Adoption intention is predominantly low: mean Behavioral Intention is 1.96 on a 1–5 scale (SD = 0.75), with 80.9% of respondents low or very low, 13.0% moderate and 6.1% high. Seven of nine hypotheses were supported. Ranked by total effect, the determinants are Effort Expectancy ($\beta = 0.345$; $p = 0.003$), Facilitating Conditions ($\beta = 0.291$; $p = 0.020$), Social Influence ($\beta = 0.250$; $p = 0.001$) and Trust ($\beta = 0.235$; $p = 0.020$). Performance Expectancy has no significant direct effect ($\beta = -0.033$; $p = 0.803$) but is the strongest antecedent of Trust ($\beta = 0.438$; $p < 0.001$), producing full mediation (indirect $\beta = 0.103$; $p = 0.019$). The model explains $R^2 = 0.653$ of Behavioral Intention and $R^2 = 0.669$ of Trust. Developers and local government should prioritize interface simplicity, logistics reliability and trust infrastructure over feature or price competition. Findings should be read with caution given narrow discriminant margins and a pronounced floor effect.

Keywords:

Agricultural e-commerce; UTAUT; PLS-SEM; Institutional buyer; B2B.

1. INTRODUCTION

Agricultural e-commerce has emerged as a strategic lever for supply chain transformation, with proven benefits in market integration, distribution efficiency, and agri-food system resilience (Zhang & Berghäll, 2021; Yang et al., 2024; Masi et al., 2025). In Indonesia, this agenda is embedded in Presidential Asta Cita Priorities No. 2 and 6 and the RPJMN 2025–2029, with the Free Nutritious Meals (MBG) program positioning institutional procurement units as strategic food distribution nodes. The B2B e-commerce model is particularly relevant as it connects farmers with institutional buyers — hotels, restaurants, hospitals, catering services, and MBG kitchens — under more stable and higher-volume transaction schemes than B2C (Li et al., 2023; Lin et al., 2022). Despite this potential, agritech startup failure rates in developing countries reach up to 80%, largely due to supply-driven platform designs that overlook institutional buyer needs (Marvin, 2019; Bethi & Deshmukh, 2023).

Research on agricultural e-commerce adoption remains dominated by supply-driven perspectives, leaving institutional buyers — the demand side — severely underrepresented (Kestane et al., 2025). The Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) provides a validated integrative framework for explaining technology adoption, with proven applicability across digital agricultural contexts (Ronaghi & Forouharfar, 2020; Larasati et al., 2024; Mkunda, 2025). This study extends UTAUT

with a Trust construct, acknowledging that B2B agricultural transactions entail higher perceived risks — transaction security, product quality assurance, and delivery reliability — not fully captured by the original model (Sholihah & Wulansari, 2025).

Three research gaps motivate this study: (i) limited studies examining B2B agricultural e-commerce adoption from the institutional buyer (demand-driven) perspective; (ii) dominance of B2C approaches that fail to represent institutional B2B complexity; and (iii) scarce quantitative evidence testing extended UTAUT adoption determinants in Eastern Indonesia, and, more specifically, an absence of studies specifying Trust as a mediator of those determinants rather than as a parallel predictor. Accordingly, this study addresses four research questions: (RQ 1) what is the level of need and adoption interest of institutional buyers in Manado City; (RQ 2) which extended UTAUT constructs shape that adoption intention, and whether Trust mediates their influence on it, tested via PLS-SEM; (RQ 3) what demand-driven conceptual platform model and visual mock-ups follow from those findings; and (RQ 4) what strategic implications arise for stakeholders. Manado City was selected as a principal agricultural distribution hub in Eastern Indonesia, with a diverse concentration of institutional buyers and proximity to key production areas (Danang et al., 2025), aligning with SDGs 2 and 9 and the national digital supply chain transformation agenda.

1.1. Agricultural E-Commerce and the B2B Model

Beyond the effects noted above, digital platforms increasingly strengthen supply-chain resilience through traceability and quality risk management (Plakantara & Karakitsiou, 2025; Lai et al., 2025), and the B2B model shows structural advantages over B2C in institutional-scale supply chains through more stable, planned and higher-volume transactions (Li et al., 2023; Lin et al., 2022). Yet agritech startup failure in developing countries remains high, attributed to supply-driven designs that neglect institutional-buyer needs and trust barriers (Marvin, 2019; Bethi & Deshmukh, 2023; Ayamga et al., 2026; Kestane et al., 2025); in Indonesia, agribusiness e-commerce adoption is constrained by organizational, technological and infrastructural factors, with the institutional-buyer demand perspective severely underrepresented (Putra et al., 2026; Hasan et al., 2025).

1.2. UTAUT Framework and the Extension of Trust

Venkatesh et al. (2003) developed UTAUT as a synthesis of eight adoption theories, positing four constructs — Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI) and Facilitating Conditions (FC) — as determinants of Behavioral Intention. The framework has been validated across digital agricultural contexts: PE and FC dominated IoT adoption in smart farming (Ronaghi & Forouharfar, 2020), PE drove precision-agriculture adoption in West Java (Larasati et al., 2024) and cold-chain adoption among vegetable producers (Mkunda, 2025), and a systematic review identifies UTAUT among the dominant frameworks in this literature (Wulan Prasetyaningtyas & Thanh Trung, 2025). This study extends UTAUT with a Trust (TR) construct on two grounds: B2B agricultural transactions carry higher perceived risks — transaction security, quality assurance, delivery reliability — than B2C, and Indonesian evidence confirms trust as a critical determinant of digital food-platform adoption not captured by the original model (Sholihah & Wulansari, 2025; Kumar et al., 2025).

1.3. Hypothesis Development

Addressing Research Question 2 — which examines the influence of extended UTAUT constructs (PE, EE, SI, FC, and Trust) on institutional buyer adoption intention — nine hypotheses are proposed within a structure that specifies both direct paths to Behavioral Intention and indirect paths through Trust. Unlike the conventional specification in which all constructs act as parallel determinants, this study positions Trust as a mediating variable. The rationale is contextual: agricultural products are perishable and their quality cannot be verified prior to delivery, so beliefs about the platform are expected to translate into intention only after passing through a confidence filter (Gefen et al., 2003; Pavlou, 2003).

PE reflects buyers' belief that the platform improves procurement performance, consistently found as the dominant adoption predictor in agritech (Mkunda, 2025; Larasati et al., 2024; Zeng et al., 2016). EE captures perceived ease of operating the platform, a decisive constraint in populations with little prior exposure to digital procurement tools (Ronaghi & Forouharfar, 2020; Larasati et al., 2024). SI reflects pressure from business partners and industry peers, which shapes e-commerce participation in agricultural settings through relational and reputational channels (Wang et al., 2025). FC reflects beliefs about available technical and logistical infrastructure, which in agri-food contexts governs whether delivery commitments can be honored at all (Lin et al., 2022; Lai et al., 2025). Trust captures institutional buyers' confidence in the platform's ability to facilitate secure transactions and deliver quality-assured products, a requirement heightened where produce is perishable and quality cannot be verified before delivery (Sholihah & Wulansari, 2025; Gefen et al., 2003).

H1a: Performance Expectancy has a positive and significant effect on Trust.

H1b: Performance Expectancy has a positive and significant effect on Behavioral Intention.

H2a: Effort Expectancy has a positive and significant effect on Trust.

H2b: Effort Expectancy has a positive and significant effect on Behavioral Intention.

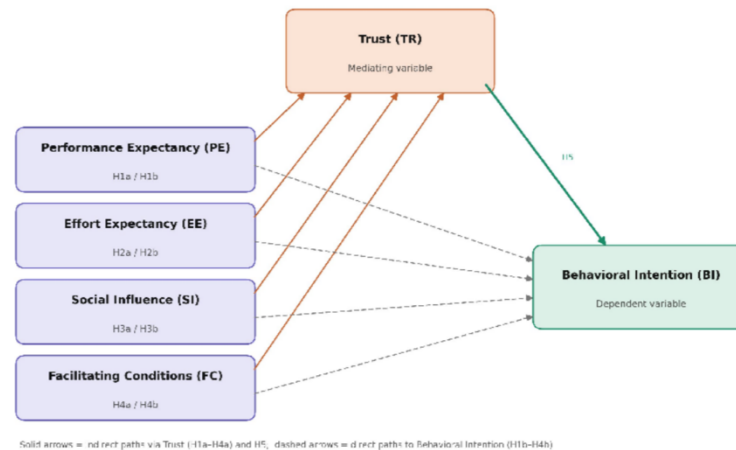
H3a: Social Influence has a positive and significant effect on Trust.

H3b: Social Influence has a positive and significant effect on Behavioral Intention.

- H4a: Facilitating Conditions have a positive and significant effect on Trust.
 H4b: Facilitating Conditions have a positive and significant effect on Behavioral Intention.
 H5 : Trust has a positive and significant effect on the Behavioral Intention of institutional buyers to adopt B2B agricultural e-commerce.

1.4. Conceptual Framework

Figure 1 presents the conceptual framework derived from the hypotheses above. Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions are specified as exogenous constructs acting on Behavioral Intention both directly and indirectly through Trust, which is positioned as the mediating construct.



Solid arrows = indirect paths via Trust (H1a-H4a) and H5; dashed arrows = direct paths to Behavioral Intention (H1b-H4b)

Figure 1. Conceptual Framework: Extended UTAUT Model with Trust as a Mediating Variable in B2B Agricultural E-Commerce Adoption. Source: Adapted from Venkatesh et al. (2003) and Venkatesh et al. (2012), extended by authors. Solid arrows denote indirect paths through Trust (H1a–H4a) and the mediator-to-outcome path (H5); dashed arrows denote direct paths to Behavioral Intention (H1b–H4b). Lavender = original UTAUT exogenous constructs; amber = extended construct (Trust); green = dependent variable.

2. RESEARCH METHOD

2.1. Research Design, Location, Population, and Sampling

This study employs a quantitative explanatory approach with a cross-sectional design to examine factors influencing institutional buyers' intention to adopt B2B agricultural e-commerce in Manado City, North Sulawesi. The target population comprises active institutional buyers — restaurants/cafes, hotels, catering services, hospitals/clinics, SPPG/MBG kitchens, modern markets and food-processing businesses — that regularly procure agricultural products at institutional scale. Because no single registry identifies all such buyers under this definition, the sampling frame was built from relevant business and institutional categories and screened by purposive (non-probability) sampling against four eligibility criteria: respondents (1) represented a Manado-based organization; (2) procured agricultural products recurrently for operations rather than household use; (3) procured at institutional-scale frequency; and (4) were involved in or knowledgeable about procurement decisions. Eligibility was defined by recurrence and frequency rather than a monetary threshold, so smaller regular buyers were not excluded; monthly procurement value is reported descriptively (Table 2). BPS figures (Kota Manado Dalam Angka 2025) indicate the general scale of the target sectors rather than an exact enumeration of eligible buyers.

A total of 120 responses were collected during June 2026 via Google Form and manual survey, then screened for careless responding (Meade & Craig, 2012; Curran, 2016). Five cases were removed — one identical across all 27 indicators ($SD = 0.000$) and four with runs of 11–19 consecutive identical items and very low variance ($SD = 0.267$ – 0.320) — leaving 115 complete responses with no missing values across six categories: restaurants/cafes (82), hotels (11), hospitals (11), catering (7), modern markets (2) and MBG kitchens (2). Restaurants/cafes thus account for 71.3% of the realized sample, reflecting the purposive strategy and their relevance to recurring fresh-input procurement rather than the population distribution; consistent with this, 60.9% procure daily, 27.8% two to three times weekly, and 87.8% spend at least IDR 5 million monthly.

The sample satisfies the 10-times rule (minimum 50 cases for the construct with the most incoming paths) and exceeds the minimum recommended by Hair et al. (2019). Post-hoc power analysis indicates approximately 80% power for standardized effects of about 0.23 or larger; smaller effects may still reach significance but are detected less reliably, as addressed in the discussion. Given the purposive design and absence of a comprehensive registry, the sample is not statistically proportional to all institutional-buyer

categories in Manado but provides evidence from eligible buyers with direct procurement experience relevant to adoption.

2.2. Research Instrument and Operationalization of Variables

The research instrument consists of a Likert 1–5 questionnaire with a total of 27 items across six constructs, scored from 1 = Strongly Disagree to 5 = Strongly Agree. The final model uses 21 active indicators following the elimination of PE2, SI1, SI2, FC3, TR1 and BI1, each of which recorded an outer loading below 0.70 or reduced the AVE of its construct. All constructs were adapted from the original UTAUT framework (Venkatesh et al., 2003), extended with Trust to capture the specific risk characteristics of B2B agricultural transactions. Table 1 presents the operational definitions and indicators for each construct.

Table 1. Operational Definition of Research Variables

Construct	Operational Definition	Indicators	Reference
PE (5 items*)	Perception that the B2B agricultural e-commerce platform enhances procurement efficiency and operational performance.	PE1: Speeds up procurement. PE2: Enables cross-supplier price comparison. PE3: Improves supply quality consistency. PE4: Reduces procurement costs. PE5: Enhances supply chain reliability	Venkatesh et al. (2003); Mkunda (2025)
EE (4 items)	Perception of ease in learning and operating the B2B agricultural e-commerce platform.	EE1: Platform easily learned by staff. EE2: Ordering process is simple. EE3: Interface easy to navigate. EE4: Usable without intensive training	Venkatesh et al. (2003); Larasati et al. (2024)
SI (4 items*)	Perception that important parties (business partners, management, industry associations) support the use of the platform.	SI1: Business partners recommend similar platforms*. SI2: Management supports digital adoption*. SI3: Industry associations promote digital procurement. SI4: Peer institutions already use B2B platforms	Venkatesh et al. (2003); Wang et al. (2025)
FC (5 items*)	Perception that technical, logistical, and organizational infrastructure supports platform use.	FC1: Regulatory and institutional support is available. FC2: Institutional devices are adequate. FC3: Internet connection is sufficient*. FC4: Delivery services are available and reliable. FC5: Technical support is accessible	Venkatesh et al. (2003); Ronaghi & Forouharfar (2020)
TR (5 items*)	Belief in transaction security, system reliability, and product quality assurance on the platform.	TR1: Platform guarantees data and transaction security*. TR2: Suppliers on the platform are reliable. TR3: Product quality assurance is transparent and verified.	Sholihah & Wulansari (2025); Kumar et al. (2025)

		TR4: Platform reputation is well established.	
		TR5: Fair dispute resolution mechanism is available	
BI (4 items*) [Dependent]	Institutional buyers' intention and readiness to use the B2B agricultural e-commerce platform.	BI1: Plans to use platform for procurement*. BI2: Will recommend platform to business partners. BI3: Intends to increase share of digital procurement. BI4: Will shift part of procurement to the B2B platform	Venkatesh et al. (2003)

Note: Item counts in the first column are pre-purification counts. All constructs were adapted from the original UTAUT framework (Venkatesh et al., 2003) and extended with Trust to capture the risk characteristics specific to B2B agricultural transactions. All items were measured on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). Items marked with an asterisk (PE2, SI1, SI2, FC3, TR1, BI1) were eliminated during outer model purification for outer loadings below 0.70 or for reducing construct AVE. The instrument comprises 27 items, of which 21 remain active in the estimated model. Source: Authors' construction based on Venkatesh et al. (2003).

2.3. Data Analysis Technique

Data were analyzed using SEM-PLS with SmartPLS 4 following a two-stage procedure (Hair et al., 2019, 2022). The first stage (outer model) evaluates convergent validity (outer loading ≥ 0.70 ; AVE ≥ 0.50), construct reliability (Cronbach's α , ρ_A and $\rho_C \geq 0.70$), and discriminant validity using both the Fornell-Larcker criterion and HTMT, applying the conservative threshold of 0.85 and the liberal threshold of 0.90 (Henseler et al., 2015). The second stage (inner model) tests the nine hypotheses through bootstrapping with 5,000 subsamples (percentile method, two-tailed, $\alpha = 0.05$) to obtain T-statistics and p-values, and computes the coefficient of determination (R^2), effect size (f^2), and inner-model collinearity (VIF). Specific indirect effects are evaluated using bias-corrected and accelerated confidence intervals. Model fit is evaluated using the Standardized Root Mean Square Residual (SRMR) with a threshold of < 0.08 .

Because the study relies on self-reported questionnaire data collected at a single point in time, the findings may be subject to common method and response biases. To mitigate this concern, respondents were assured of confidentiality, items were presented using neutral wording, and common method bias was assessed using Harman's single-factor diagnostic. The first unrotated factor accounted for 48.8% of the variance, marginally below the 50% threshold, indicating that common method bias was present but not dominant.

3. RESULTS AND DISCUSSION

Results are organized into four blocks corresponding to the research questions: respondent profile and descriptive analysis (Sections 3.1–3.2; RQ 1), measurement and structural model evaluation (Sections 3.3–3.4; RQ 2), conceptual model and platform design (Sections 3.5–3.7; RQ 3), and strategic implications (Section 3.8; RQ 4).

3.1. Respondent Profile

Table 2. Respondent Profile (N = 115)

Characteristic	Category	n	%
Institution Type	Restaurant / Cafe	82	71.3
	Hotel	11	9.6
	Hospital	11	9.6
	Catering	7	6.1
	Modern Market	2	1.7
	MBG Kitchen	2	1.7
Years of Operation	< 1 year	20	17.4
	1–2 years	13	11.3
	2–5 years	21	18.3
	> 5 years	61	53.0
Purchase Frequency	Daily	70	60.9

	2–3 times per week	32	27.8
	Weekly	7	6.1
	Monthly	5	4.3
	Twice monthly	1	0.9
Monthly Purchase Value	< IDR 5 million	14	12.2
	IDR 5–20 million	48	41.7
	IDR 20–50 million	27	23.5
	IDR 50–100 million	26	22.6
	> IDR 100 million	0	0.0
Primary Purchase Channel	Traditional market	83	72.2
	Established supplier	29	25.2
	Other	3	2.6
E-Commerce Experience	Never used	108	93.9
	Has used	7	6.1

Note: Percentages are calculated over the full analytical sample (N = 115) and sum to 100% within each characteristic. Primary Purchase Channel records only the single channel each respondent identified as principal; because institutional buyers commonly combine channels, these figures understate the share using any given channel. Source: Primary data analysis (2026).

Respondents were dominated by Restaurants and Cafes (71.3%), followed by Hotels and Hospitals (9.6% each), Catering services (6.1%), and Modern Markets and MBG Kitchens (1.7% each). Slightly over half had operated for more than five years (53.0%). Purchasing is highly frequent — 60.9% procure agricultural products daily and a further 27.8% two to three times per week — and procurement value is correspondingly substantial: 87.8% spend at least IDR 5 million per month, with the modal band at IDR 5–20 million (41.7%) and a further 46.1% procuring above IDR 20 million, distributed almost evenly between the IDR 20–50 million (23.5%) and IDR 50–100 million (22.6%) bands. Only 12.2% spend below IDR 5 million per month, and no respondent exceeds IDR 100 million. Nearly three-quarters currently source through traditional markets (72.2%) and a quarter through established suppliers (25.2%); only 6.1% had ever used e-commerce for agricultural purchases. This combination — high-frequency, mid-to-high-value, physically mediated procurement with almost no prior platform exposure — characterizes the institutional segment under study and is central to interpreting the findings that follow. It also establishes that the low adoption intention reported below cannot be attributed to transaction volumes too small to justify digital procurement: the segment already transacts at a scale at which platform intermediation would ordinarily be economically attractive, which shifts the explanatory burden onto the perceptual and infrastructural barriers modeled in the subsequent sections.

3.2. Descriptive Analysis: Level of Need and Adoption Interest (RQ 1)

Table 3. Distribution of Behavioral Intention Categories (N = 115)

Category	Score Range	n	Percentage (%)	Interpretation
Very Low	≤ 1.80	61	53.0	Very weak adoption intention
Low	1.81 – 2.60	32	27.8	Weak adoption intention
Moderate	2.61 – 3.40	15	13.0	Adoption intention not yet formed
High	3.41 – 4.20	7	6.1	Strong adoption intention
Very High	> 4.20	0	0.0	Very strong adoption intention
Total		115	100.0	

Note: Behavioral Intention is the mean of the three retained items (BI2–BI4). Categories are derived from the five-point Likert scale using an equal class interval of 0.80. Percentages may not sum to 100.0 due to rounding. Source: Primary data analysis (2026).

A total of 80.9% of respondents fell into the low or very low Behavioral Intention categories, indicating generally weak adoption intention among institutional buyers. A further 13.0% were classified in the moderate category, 6.1% reached the high category, and no respondent reached the very high category. Overall, the distribution suggests that agricultural e-commerce adoption remains at an early stage within the sampled institutions. The need dimension of RQ 1 is addressed further in Section 3.5, where respondents stated feature priorities are reported. Read together with the near-absence of prior experience with agricultural e-commerce in this population, the pattern indicates a market that is underdeveloped rather than merely untapped: the great majority of institutional buyers do not yet display adoption intention, while the 6.1% in the high category constitute a small but real early-adopter base.

Comparison of construct means indicates that all UTAUT constructs scored below the midpoint of the five-point scale, suggesting generally weak perceptions toward agricultural e-commerce adoption. Social Influence recorded the highest mean (M = 2.35), followed by Performance Expectancy (M = 2.14), Trust (M = 2.01), Facilitating Conditions (M = 1.94), and Effort Expectancy (M = 1.85). Behavioral Intention itself averaged 1.96 (SD = 0.75), placing it within the same narrow band as the constructs that predict it. These

descriptive findings are consistent with the structural model, in which Effort Expectancy emerged as the strongest predictor of Behavioral Intention despite exhibiting the lowest average perception. Differences between adjacent constructs are small and are therefore reported as an ordering rather than as substantively distinct levels.

Table 4. Mean Behavioral Intention by Institution Type

Institution Type	n	Mean BI	SD	Category
Modern Market	2	2.83	1.18	Moderate
Hotel	11	2.30	0.72	Low
Hospital	11	2.03	0.88	Low
Restaurant / Cafe	82	1.92	0.73	Low
Catering	7	1.81	0.57	Low
MBG Kitchen	2	1.17	0.24	Very Low
Overall	115	1.96	0.75	Low

Note: Behavioral Intention is the mean of the three retained items (BI2–BI4); categories follow the classification in Table 3. Cell sizes for Modern Market (n = 2), MBG Kitchen (n = 2) and Catering (n = 7) are small, and Restaurants/Cafes account for 71.3% of the sample, so the aggregate mean is dominated by a single segment. Between-segment comparisons are descriptive only and were not tested inferentially. Source: Primary data analysis (2026).

Behavioral Intention also varies across institutional types. Modern Markets recorded the highest mean (M = 2.83), followed by Hotels (M = 2.30) and Hospitals (M = 2.03), while Catering services (M = 1.81) and MBG Kitchens (M = 1.17) recorded the lowest. No segment reaches the scale midpoint of 3.00, and only Modern Markets — represented by two respondents — rise above the Low band. Because Restaurants and Cafes constitute 71.3% of the sample, the aggregate mean is dominated by that segment, and the ordering across institution types is best read as differences in degree within a uniformly low range rather than as evidence of a receptive segment.

Table 5. Barriers to B2B Agricultural E-Commerce Adoption (N = 115)

Barrier	n	Percentage (%)	Prevalence Level
Preference for established fixed suppliers	36	31.3	Very high
No suitable platform yet available	26	22.6	High
Concern over delivery delays	24	20.9	High
Uncertainty about product quality	20	17.4	Moderate
Concern over transaction security	7	6.1	Low
Limited internet infrastructure	1	0.9	Very low
Lack of digital knowledge	1	0.9	Very low
Other	0	0.0	None

Note: Percentages are calculated over the full analytical sample (N = 115). The instrument permitted multiple responses, so the categories are not mutually exclusive in principle; in this sample, however, the recorded barrier responses total 115, equal to the analytical sample, and the percentage column therefore approximates 100%. Barrier data were captured through the online instrument, and respondents without recorded barrier data are treated as not having cited any barrier, so the reported percentages are conservative lower bounds on prevalence. Prevalence levels are descriptive labels assigned by the authors and carry no inferential status. Source: Primary data analysis (2026).

The barrier structure is relational rather than technological. Supplier loyalty (31.3%), delivery reliability (20.9%) and product quality uncertainty (17.4%) all concern confidence in the transacting party, whereas infrastructure and digital literacy barriers register at only 0.9% each. Institutional buyers are not deterred by technology; they are deterred by the risk of replacing a supplier relationship they can physically verify with one they cannot. A further 22.6% report that no platform suited to institutional needs currently exists — an expression of unmet demand rather than resistance. These figures should be read as conservative lower bounds on prevalence.

The distribution raises an interpretive question governing how the study should be read: if 80.9% of buyers express low or very low intention, is platform design still warranted? The mean could reflect either an evaluated rejection of the B2B model or a pre-exposure baseline in a population that has not encountered the object being evaluated. Four features of the data favour the second reading. First, the referent: intention was elicited where 93.9% had never used any agricultural e-commerce platform and 72.2% procure through traditional markets, so scores registering the difficulty of imagining an unencountered technology (Venkatesh et al., 2003) are better read as intention not yet formed — a reading supported by the 19.1% who still reached moderate or high bands despite near-uniform absence of prior exposure. Second, the barrier composition: the second most-cited barrier is that no platform suited to institutional needs currently exists (22.6%), a statement about platform supply rather than about the desirability of platform-mediated procurement.

Third, the character of the remaining barriers: preference for established suppliers (31.3%), delivery delays (20.9%) and product-quality uncertainty (17.4%) together account for 69.6% of barrier responses and each concerns confidence in the transacting party — all within the reach of platform design (escrow, verified grading, delivery guarantees, incumbent-supplier onboarding; Sections 3.5–3.7) — whereas the barriers design cannot address (limited internet, lack of digital knowledge) register 1.8% combined. Fourth, the economic substrate: buyers already procure at intermediation-viable scale (60.9% purchase daily; 87.8% spend $\geq$ IDR 5 million monthly; 46.1% exceed IDR 20 million), so low intention cannot be attributed to insufficient volume. These observations do not establish latent demand; they establish only that the low mean is consistent with a pre-exposure population facing design-addressable barriers, and that evaluated rejection is not supported by the barrier structure. The distinction is testable by a pre-post exposure design re-eliciting intention after prototype interaction (Section 3.8.3); pending that test, the structural results below are treated as a specification of the conditions under which intention could form rather than as a forecast of uptake.

3.3. Measurement Model Evaluation / Outer Model (RQ 2)

Table 6. Outer Loading Summary by Construct

Construct	Indicators	Loading Range	Remarks
Performance Expectancy (PE)	4*	0.732 – 0.858	PE2 eliminated
Effort Expectancy (EE)	4	0.780 – 0.897	All retained
Social Influence (SI)	2*	0.825 – 0.887	SI1 and SI2 eliminated
Facilitating Conditions (FC)	4*	0.771 – 0.827	FC3 eliminated
Trust (TR)	4*	0.729 – 0.839	TR1 eliminated
Behavioral Intention (BI)	3*	0.763 – 0.833	BI1 eliminated

Note: Loading ranges refer to retained indicators only. Constructs marked with an asterisk had one or more indicators eliminated during outer model purification (PE2, SI1, SI2, FC3, TR1, BI1) for outer loadings below 0.70 or for reducing construct AVE, meeting the condition under which indicator removal is warranted (Hair et al., 2019). All 21 retained indicators load at or above 0.729, ranging from 0.729 (TR2) to 0.897 (EE3). Social Influence retains only two indicators, and its reliability estimates should be read in light of that constraint (see Table 7). Source: SmartPLS 4 output (2026).

Table 7. Construct Reliability and Validity

Construct	Cronbach's α	ρ_A	ρ_C	AVE
Behavioral Intention	0.727	0.732	0.846	0.646
Effort Expectancy	0.866	0.884	0.909	0.714
Facilitating Conditions	0.824	0.826	0.883	0.654
Performance Expectancy	0.808	0.817	0.875	0.636
Social Influence	0.641	0.658	0.847	0.734
Trust	0.797	0.816	0.867	0.621

Note: α = Cronbach's alpha; ρ_A = Dijkstra–Henseler reliability coefficient ρ_A ; ρ_C = composite reliability ρ_C ; AVE = average variance extracted. Thresholds applied: $\alpha \geq 0.70$; $\rho_A \geq 0.70$; $\rho_C \geq 0.70$; AVE ≥ 0.50 (Hair et al., 2019). Social Influence retains only two indicators after purification and falls below the 0.70 benchmark on α and ρ_A ; the grounds on which it is nevertheless retained, and the qualifications attaching to its reliability estimates, are set out in the text below. Source: SmartPLS 4 output (2026).

Convergent validity is established for all six constructs: every AVE (0.621–0.734) lies comfortably above 0.50, and composite reliability ρ_C ranges from 0.847 to 0.909. Reliability is uneven, however. Cronbach's α ranges from 0.641 to 0.866 and ρ_A from 0.658 to 0.884, and Social Influence falls below the 0.70 benchmark on both coefficients ($\alpha = 0.641$; $\rho_A = 0.658$). This is an expected consequence of retaining only two indicators after purification, since both α and ρ_A are downward-biased for very short scales. Social Influence was initially measured with four indicators (SI1–SI4); SI1 and SI2 were removed during outer-model purification for low outer loadings, leaving SI3 and SI4 as the two retained indicators, so Social Influence is a two-item construct rather than a single-item measure. The corresponding ρ_C of 0.847 does not by itself resolve the matter, because composite reliability computed from PLS loadings is upward-biased when a construct retains only two indicators and therefore overstates reliability in precisely this case. Social Influence is nevertheless retained, on three grounds: its AVE of 0.734 is the highest in the model, both retained indicators load above 0.82, and it shows the widest discriminant separation from all other constructs on the HTMT criterion (Table 8). The two-item measurement is acknowledged as a limitation of the study.

Table 8. Heterotrait-Monotrait Ratio (HTMT) Matrix

Construct	BI	EE	FC	PE	SI
Behavioral Intention (BI)	—				
Effort Expectancy (EE)	0.7625	—			
Facilitating Conditions (FC)	0.8348	0.8252	—		
Performance Expectancy (PE)	0.8489	0.8487	0.8405	—	
Social Influence (SI)	0.7715	0.3822	0.6105	0.7257	—
Trust (TR)	0.8149	0.8142	0.8314	0.8482	0.7120

Note: HTMT values are reported for all fifteen construct pairs; the matrix is lower-triangular. Following Henseler et al. (2015), both the conservative threshold of 0.85 and the liberal threshold of 0.90 are applied, consistent with the procedure stated in Section 2.3. No construct pair exceeds the conservative threshold of 0.85, and none approaches the liberal threshold of 0.90. The three highest values are PE↔BI (0.8489), PE↔EE (0.8487) and PE↔TR (0.8482); no pair reaches 1.00. Social Influence separates most widely from every other construct (HTMT < 0.78). Discriminant validity is therefore established for all fifteen construct pairs on the HTMT criterion, although the narrow margins on the Performance Expectancy pairings are noted, and the structural estimates reported in Tables 10–12 are interpreted accordingly. Source: SmartPLS 4 output (2026).

Table 9. Fornell-Larcker Criterion

Construct	BI	EE	FC	PE	SI	TR
Behavioral Intention	0.8039					
Effort Expectancy	0.7028	0.8448				
Facilitating Conditions	0.7315	0.7884	0.8085			
Performance Expectancy	0.6898	0.7441	0.7831	0.7977		
Social Influence	0.5255	0.3058	0.4557	0.5418	0.8568	
Trust	0.7099	0.6934	0.7151	0.7862	0.5205	0.7877

Note: Diagonal values are the square root of AVE; off-diagonal values are latent variable correlations. Values are reported to four decimal places because the discriminant margins discussed below are narrower than three-decimal rounding would reveal. Discriminant validity requires each diagonal value to exceed all correlations in its row and column. The criterion is formally satisfied for all six constructs, but the margin is negligible for Trust and Performance Expectancy: their mutual correlation of 0.7862 sits only 0.0015 below the square root of AVE for Trust (0.7877) and 0.0115 below that for Performance Expectancy (0.7977). The separation between these two constructs is therefore narrow, although it is formally satisfied, and this reading is consistent with the HTMT value of 0.8482 reported in Table 8, which remains below the conservative 0.85 threshold. Source: SmartPLS 4 output (2026).

Two complementary discriminant-validity procedures converge (detail in the Table 8–9 notes): Fornell-Larcker is satisfied for all six constructs, though only marginally for Trust and Performance Expectancy, and HTMT is satisfied for all fifteen pairs, with the highest values — PE↔BI (0.8489), PE↔EE (0.8487) and PE↔TR (0.8482) — remaining below the conservative 0.85 threshold. Discriminant validity is therefore established, but the narrow margins around Performance Expectancy warrant cautious interpretation of the structural results.

Diagnostic analysis clarifies the nature of the problem. Mean inter-item correlations within constructs (0.470–0.617) exceed the mean between-construct correlation (0.420; range 0.206–0.533), so items are more cohesive within their own construct and the constructs are not undifferentiated. Harman’s single-factor test yields 48.8% of variance on the first unrotated factor, marginally below 50%, indicating common method bias that is present but not dominant. The comparatively high HTMT values for the Performance Expectancy and Facilitating Conditions pairings are more plausibly attributable to the pronounced floor effect: when most responses cluster at the lower end of the scale, between-construct correlations inflate uniformly. This is a characteristic of the pre-adoption population rather than an instrument defect, but it constrains inference and is reported transparently.

3.4. Structural Model Evaluation and Hypothesis Testing (RQ 2)

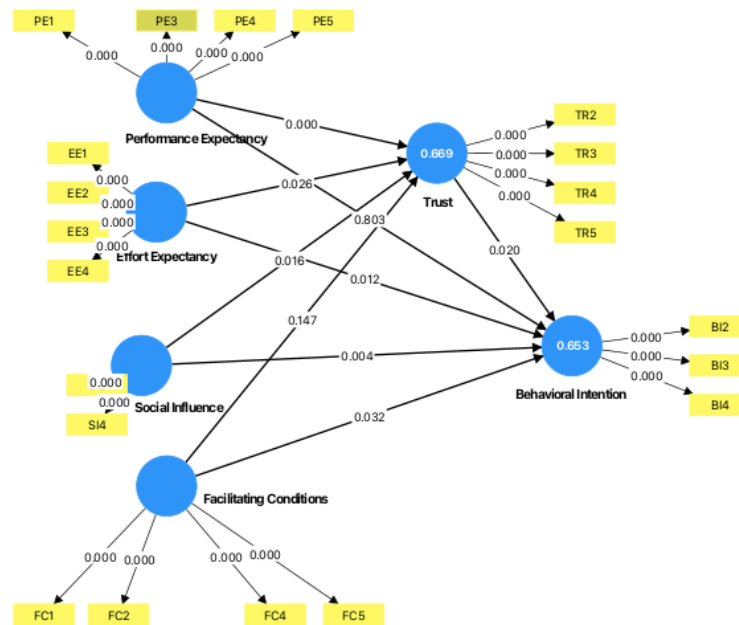


Figure 2. Final Structural Model Bootstrapping Results (5,000 Bootstrap Subsamples). Source: SmartPLS 4 output, processed by the researchers (2026). Values on the structural paths are p-values from bootstrapping with 5,000 subsamples; values inside the endogenous constructs are R² (Trust = 0.669; Behavioral Intention = 0.653). Corresponding path coefficients and T-statistics are reported in Table 10.

Table 10. Direct Path Coefficients and Hypothesis Testing

Hypothesis	Path	β	T	p	f²	Decision
H1a	Performance Expectancy → Trust	0.4377	4.161	< 0.001	0.151	Supported
H3b	Social Influence → Behavioral Intention	0.2123	2.850	0.0044	0.065	Supported
H2b	Effort Expectancy → Behavioral Intention	0.2937	2.501	0.0124	0.049	Supported
H3a	Social Influence → Trust	0.1582	2.411	0.0160	0.042	Supported
H5	Trust → Behavioral Intention	0.2349	2.325	0.0201	0.067	Supported
H2a	Effort Expectancy → Trust	0.2183	2.228	0.0259	0.044	Supported
H4b	Facilitating Conditions → Behavioral Intention	0.2607	2.141	0.0323	0.033	Supported
H4a	Facilitating Conditions → Trust	0.1282	1.452	0.1465	0.023	Not supported
H1b	Performance Expectancy → Behavioral Intention	-0.0327	0.249	0.8030	0.000	Not supported

Note: Estimates were obtained by bootstrapping with 5,000 subsamples using the percentile method, two-tailed, at a 5% significance level. Rows are ordered by ascending p-value rather than by hypothesis number. The f² column reports Cohen's effect size for each structural path, computed on the raw model estimates; values of 0.02, 0.15 and 0.35 denote small, medium and large effects respectively. Seven of nine hypotheses are supported. Inner-model VIF values range from 1.503 to 2.950, all below the recommended threshold of 3.30, indicating that multicollinearity among the exogenous constructs is not a concern. The negative but non-significant coefficient on H1b instead reflects the full mediation of Performance Expectancy's effect on Behavioral Intention through Trust (see Table 11), rather than collinearity among predictors. Source: SmartPLS 4 output (2026).

Table 11. Specific Indirect Effects Through Trust

Mediation Path	β	T	p	BCa 2.5%	BCa 97.5%	Mediation Type
PE → Trust → BI	0.1028	2.349	0.0189	0.0286	0.2034	Full mediation
EE → Trust → BI	0.0513	1.534	0.1250	0.0040	0.1418	Not established
SI → Trust → BI	0.0372	1.533	0.1254	0.0044	0.1084	Not established
FC → Trust → BI	0.0301	1.040	0.2982	-0.0048	0.1116	No mediation

Note: Estimates were obtained by bootstrapping with 5,000 subsamples. BCa = bias-corrected and accelerated confidence interval (95%, two-tailed). Only the Performance Expectancy path constitutes established mediation: its direct effect is non-significant (Table 10) while its indirect effect is significant, which corresponds to full mediation under Hair et al. (2019). For Effort Expectancy and Social Influence, although the BCa confidence intervals exclude zero, the reported p-values exceed 0.05; consistent with the p-value-based decision rule adopted in this study, mediation is not claimed for these paths. The Facilitating Conditions interval includes zero and its p-value is non-significant, indicating no mediation. Source: SmartPLS 4 output (2026).

Table 12. Total Effects on Behavioral Intention

Construct	Total β	T	p	Decision
Effort Expectancy	0.3450	2.994	0.0028	Significant
Facilitating Conditions	0.2908	2.328	0.0199	Significant
Social Influence	0.2495	3.404	0.0007	Significant
Trust	0.2349	2.325	0.0201	Significant
Performance Expectancy	0.0702	0.555	0.5787	Not significant

Note: Total effect equals the direct effect on Behavioral Intention plus the indirect effect transmitted through Trust. Trust has no indirect component; therefore, its total effect equals its direct effect (Table 10). Estimates were obtained using bootstrapping with 5,000 subsamples (percentile method, two-tailed, $\alpha = 0.05$). Rows are ordered by descending total effect (β). The model explains 65.3% of the variance in Behavioral Intention ($R^2 = 0.653$; adjusted $R^2 = 0.637$) and 66.9% of the variance in Trust ($R^2 = 0.669$; adjusted $R^2 = 0.657$). The standardized root mean square residual (SRMR) is 0.0885, above the 0.08 threshold applied in Section 2.3 and therefore indicating marginal approximate fit. Source: SmartPLS 4 output (2026).

The model shows substantial explanatory power ($R^2 = 0.653$ for Behavioral Intention, $R^2 = 0.669$ for Trust; full statistics in the Table 10–12 notes), with SRMR = 0.0885 indicating marginal approximate fit, so estimates are read with corresponding caution. Multicollinearity is not a concern (inner VIF 1.503–2.950, all below 3.30), and effect sizes are modest — the largest being PE $\rightarrow$ Trust ($f^2 = 0.151$, medium range), with all other paths small ($f^2 = 0.000$ – 0.067).

Seven of the nine proposed hypotheses were supported. Effort Expectancy emerged as the strongest overall determinant of Behavioral Intention, exhibiting the largest total effect ($\beta = 0.345$, $p = 0.0028$). This effect reflects the combined contribution of a significant direct effect ($\beta = 0.294$, $p = 0.0124$) and a positive indirect effect transmitted through Trust. Facilitating Conditions ranked second ($\beta = 0.291$, $p = 0.0199$), followed by Social Influence ($\beta = 0.250$, $p = 0.0007$) and Trust itself ($\beta = 0.235$, $p = 0.0201$). These findings indicate that users' intentions to adopt the platform are primarily driven by perceived ease of use, enabling conditions, and social encouragement, while trust serves as an important mechanism that translates favorable perceptions into behavioral intention. Consistent with this role, Performance Expectancy was the strongest antecedent of Trust in the model ($\beta = 0.438$, $p < 0.001$; $f^2 = 0.151$).

The bootstrap results indicate that the indirect effect of Performance Expectancy (PE) on Behavioral Intention (BI) through Trust is positive and statistically significant based on the reported p-value ($\beta = 0.1028$, $t = 2.349$, $p = 0.0189$). The corresponding 95% bias-corrected and accelerated (BCa) confidence interval ranges from 0.0286 to 0.2034, which does not include zero, providing additional support for the indirect effect. For the indirect effects involving Effort Expectancy (EE) and Social Influence (SI), the reported p-values exceed the 0.05 significance threshold ($p = 0.1250$ and $p = 0.1254$, respectively). Although their reported BCa confidence intervals do not include zero, the hypothesis decisions in this study are based on the reported p-values using a 5% significance level. Accordingly, the indirect effects of EE and SI through Trust are not considered statistically significant. Given that multicollinearity was not evident (inner-model VIF < 3.30) and discriminant validity was established, the non-significant direct PE $\rightarrow$ BI effect ($\beta = -0.033$, $p = 0.8030$) suggests that Performance Expectancy influences Behavioral Intention primarily through enhancing users' Trust rather than through a direct path.

Post-hoc power analysis further clarifies the two unsupported hypotheses. With a sample size of 115, the model achieved approximately 80% statistical power for detecting standardized path coefficients of around 0.23 or larger at the 5% significance level. Detecting an effect of the size estimated for Facilitating Conditions $\rightarrow$ Trust would require approximately 377 respondents. The Performance Expectancy $\rightarrow$ Behavioral Intention coefficient, by contrast, is negative and close to zero, so no realistic sample size would establish the hypothesized positive effect. The Facilitating Conditions path is therefore best read as underpowered rather than absent, whereas the Performance Expectancy path is better read as the absence of a direct effect, consistent with the full mediation through Trust reported in Table 11. These two null results are theoretically informative rather than anomalous. The absence of a direct Performance Expectancy effect contrasts with agritech studies in which Performance Expectancy was the dominant direct predictor of adoption (Mkunda, 2025; Larasati et al., 2024); in the present high-risk B2B procurement setting, performance beliefs appear to shape intention only after being channelled through Trust, consistent with trust-centred accounts of online transaction behaviour (Gefen et al., 2003; Pavlou, 2003). The non-significant Facilitating Conditions $\rightarrow$ Trust path, by

contrast, is consistent with Facilitating Conditions acting as an enabling infrastructural condition that influences Behavioral Intention directly ($\beta = 0.261$, $p = 0.0323$) rather than as a source of trust, so that its indirect route through Trust remains weak and, at the present sample size, underpowered.

3.5. Conceptual Model Formulation

Alongside the barrier data, respondents rated the importance of seven candidate platform features on a five-point scale (1 = most important, 5 = least important). Table 13 reports the five features for which response data are available, ranked by mean importance.

Table 13. Stated Platform Feature Priorities

Rank	Platform Feature	Mean	SD	% scoring 1–2	Linked Construct
1	Real-time delivery tracking	1.55	0.92	93.0	Facilitating Conditions
2	Price negotiation and bulk order offer	1.64	0.82	88.7	Performance Expectancy
3	Digital quality verification and grading	1.93	1.03	80.0	Trust
4	Flexible payment (terms, credit, transfer, COD)	2.44	1.33	61.7	Facilitating Conditions
5	Scheduled ordering and long-term contracts	3.00	1.09	28.7	Performance Expectancy

Note: $N = 115$; all respondents in the analytical sample provided feature-priority data. Importance was rated on a five-point scale from 1 (most important) to 5 (least important), so lower means indicate higher priority; the scale is a rating rather than a forced ranking, and the “Rank” column reports the ordering by mean. “% scoring 1–2” is the share of the 115 respondents assigning the feature a score of 1 or 2. Two of the seven candidate features — real-time price catalog and automated transaction history reporting — are omitted because no response data were recorded for them in the instrument as administered, a separate matter from the completeness of the 27 construct indicators reported in Section 2.1; the priorities should accordingly be read as partial. The “Linked Construct” column is an interpretive mapping by the authors and was not derived from the structural model. Source: Primary data analysis (2026).

The stated priorities converge with the structural results, although both derive from the same instrument and therefore share common method variance. Two of the three highest-scoring features operationalize constructs that significantly predict adoption intention: real-time delivery tracking is a direct expression of Facilitating Conditions (direct $\beta = 0.261$; total $\beta = 0.291$), and digital quality verification is a direct expression of Trust ($\beta = 0.235$). Both also correspond to two of the four most frequently cited barriers — concern over delivery delays (20.9%) and uncertainty about product quality (17.4%). Equally informative is the feature scoring lowest: scheduled ordering with long-term contracts was assigned a score of 1 or 2 by only 28.7% of respondents, despite standing orders being a standard assumption in B2B agritech design. This is consistent with the procurement profile identified earlier, in which buyers purchase daily and at substantial monthly value yet source almost entirely through spot transactions in traditional markets; such buyers seek per-transaction reliability rather than contractual commitment, having built their operations around the flexibility of daily market sourcing rather than around forward obligations. Feature specifications in the following subsections are therefore weighted toward delivery assurance, quality verification and price negotiation, and away from contract-oriented functionality.

Low Adoption Intention Alongside Strongly Articulated Feature Requirements. Read alongside the feature-priority assessment, the low Behavioral Intention ($M = 1.96$) coexists with sharply differentiated preferences: real-time delivery tracking drew the strongest priority (93.0% scoring 1–2; $M = 1.55$), followed by price negotiation and bulk-order offers (88.7%; $M = 1.64$) and digital quality verification (80.0%; $M = 1.93$), while scheduled ordering with long-term contracts drew only 28.7%. Low intention alongside concrete, differentiated requirements is therefore better read as conditional demand than as blanket rejection of digital procurement — buyers remain reluctant toward a generic platform yet articulate specific needs around delivery uncertainty, price negotiation and quality assurance.

The two measures also draw on different bases: adoption intention requires judging an object most respondents have not encountered (Section 3.2.1), whereas feature priorities draw on procurement experience buyers already possess, since the barriers in Table 5 arise in their current sourcing. The appropriate response to a low mean is thus not to conclude that digitalization is unnecessary, but to ask whether a platform meeting the stated requirements shifts intention — which Sections 3.6 and 3.7 address as a design specification. Because both figures derive from the same instrument and the feature ranking is partial, the contrast is offered as interpretation rather than as an independent test.

The conceptual model adopts a demand-driven approach, positioning institutional buyer needs as the foundation for platform design. It is structured around five dimensions corresponding to the extended UTAUT constructs, each weighted by the empirical support it received in the structural model rather than treated as

equally important, and each mapped to platform feature recommendations, cross-checked against respondents' own stated feature priorities (Table 13) and presented in Table 14.

Table 14. Conceptual Model Dimensions and Platform Feature Recommendations

Model Dimension	Empirical Basis	Platform Feature Recommendations	Development Priority
Usability (Effort Expectancy)	EE → BI significant ($\beta = 0.294$; $p = 0.0124$) and the strongest determinant by total effect (0.345). Lowest construct mean in the study (1.85), and 93.9% of buyers have never used an agricultural e-commerce platform.	a. Simple mobile-first interface. b. Maximum four-step ordering. c. Small-lot ordering without large minimum quantities. d. One-click recurring order for daily procurement. e. Institution-specific onboarding	Very High (MVP core; largest deficit and largest lever)
Logistics & System Support (Facilitating Infrastructure)	FC → BI significant ($\beta = 0.261$; $p = 0.0323$; total $\beta = 0.291$). Construct mean 1.94. Delivery delays cited by 20.9% of buyers. Real-time delivery tracking is the highest-rated feature overall (mean 1.55; 93.0% scoring 1–2).	a. Real-time GPS delivery tracking. b. Guaranteed delivery windows with automatic compensation on breach. c. Flexible scheduling (same-day / H+1). d. Local logistics partner integration. e. Failure alerts and rescheduling	Very High (MVP core)
Digital Trust	Trust → BI significant ($\beta = 0.235$; $p = 0.0201$) and sole channel converting Performance Expectancy into intention (indirect $\beta = 0.103$; BCa CI [0.029, 0.203]). Construct mean 2.01. Quality verification ranked third (mean 1.93; 80.0% scoring 1–2); quality uncertainty cited by 17.4%.	a. Digital quality verification and supplier grading. b. Product inspection photos at packing stage. c. Right of inspection on delivery with full refund. d. Escrow payment. e. Verified delivery and dispute records	Very High (MVP core)
Functional Value (Value Proposition)	PE → BI not significant directly ($\beta = -0.033$; $p = 0.8030$) but strongest antecedent of Trust ($\beta = 0.438$; $p < 0.001$; $f^2 = 0.151$). Construct mean 2.14. Price negotiation and bulk-order offer ranked second overall (mean 1.64; 88.7% scoring 1–2).	a. Price negotiation and bulk-order offer. b. Real-time multi-supplier price comparison. c. Cost-savings dashboard vs. traditional market prices d. Auditable transaction and delivery history	High (delivered via Trust)
Social Network & Community (Social Ecosystem)	SI → BI significant ($\beta = 0.212$; $p = 0.0044$) with the cleanest discriminant separation of any construct. Highest construct means (2.35). Preference for	a. Onboarding of buyers' own existing suppliers.	Medium–High (reduces relational switching cost)

- established suppliers is the most cited barrier (31.3%).
- b. Favorite Supplier and Whitelist feature.
 - c. Institutional referral credit program.
 - d. Buyer community forum by institution type

Note: Development priority is assigned by the authors on the combined basis of total effect on Behavioral Intention (Table 12), construct mean, stated feature priority (Table 13) and barrier prevalence (Table 5); it reflects a development-sequencing judgment rather than a statistical ranking. Rows are ordered by that development priority; the ranking by total effect on Behavioral Intention is reported separately in Table 12 (EE 0.345; FC 0.291; SI 0.250; Trust 0.235; PE 0.070). Construct means are on a 1–5 scale (SI 2.35; PE 2.14; Trust 2.01; FC 1.94; EE 1.85). Feature recommendations are design proposals and were not empirically tested. PE = Performance Expectancy; EE = Effort Expectancy; FC = Facilitating Conditions; SI = Social Influence; BI = Behavioral Intention. Source: Authors' synthesis of the empirical findings (2026).

A pattern worth noting is that the construct with the lowest mean, Effort Expectancy (1.85), is simultaneously the one with the largest total effect on adoption intention ($\beta = 0.345$). Perceived difficulty of use is therefore not a peripheral concern but a central one. Conversely, Performance Expectancy scores comparatively higher (2.14) yet exerts no direct influence, indicating that convincing buyers of the benefit is not the binding constraint. The stated feature priorities point in the same direction: buyers rank delivery assurance and quality verification above contractual and scheduling functionality, so simplification and resource support should precede value communication in the development sequence.

3.6. Platform Architecture

The five model dimensions are operationalized through a six-layer platform architecture (Table 15), designed with modular principles to enable incremental development.

Table 15. Six-Layer B2B Agricultural E-Commerce Platform Architecture

Platform Layer	Actors / Components	Core Functions	Link to Empirical Findings
User Layer	Institutional Buyers (hotels, restaurants, catering, hospitals, SPPG/MBG kitchens, modern markets, food industry)	Institutional registration; procurement profile management; order placement and transaction history	Entry point for all UTAUT dimensions; interacts with all platform modules
Transaction Layer	Payment gateway; escrow system; digital invoicing module	Secure payment processing; escrow fund management; automated digital invoicing	Addresses transaction security barrier; core Trust dimension ($\beta = 0.235$) and the conversion channel for Performance Expectancy
Product Layer	Suppliers/farmers; product curators; quality certification verification system	Standardized agricultural product catalog; quality certification display; real-time multi-supplier price comparison	Addresses product quality uncertainty; converts PE ($\beta = 0.438 \rightarrow$ Trust) into intention via Trust ($\beta = 0.235$)
Logistics Layer	Delivery partners; drivers; real-time GPS tracking system	Flexible delivery scheduling; real-time GPS tracking; SLA management; delivery failure alerts	Addresses dominant delivery delay barrier; core FC dimension (direct $\beta = 0.261$; total $\beta = 0.291$)
Data & Analytics Layer	BI systems; admin dashboard; periodic reporting module	Institutional purchasing pattern analytics; supplier recommendations; cost-efficiency reports	Supports PE, which operates on intention only through Trust (indirect $\beta = 0.103$); basis for platform improvement
Ecosystem Layer	Local government; Department of Agriculture; buyer community; MBG program (SPPG units)	MBG procurement integration; reference price standardization; supplier grading standards; community forum	Supports platform legitimacy; anchors SI dimension (direct $\beta = 0.212$; total $\beta = 0.250$)

Note: The architecture is a conceptual design output at TRL 2; no layer has been implemented or tested. Layers follow modular design principles so that each can be developed incrementally. Path coefficients cited in the final column are drawn from Tables 10 and 12 and indicate which empirical finding each layer is intended to address; they do not constitute evidence for the architecture itself. PE = Performance Expectancy; FC = Facilitating Conditions; SI = Social Influence; SLA = service level agreement; MBG = Makan Bergizi Gratis; SPPG = Satuan Pelayanan Pemenuhan Gizi. Source: Authors' design based on the empirical findings (2026).

3.7. Visual Mock-Up of the AgroB2B Platform

As a TRL 2 output, eight evidence-based mock-up screens were developed, each traceable to a specific UTAUT finding and shown together in Figure 3. The design consistently subordinates functional and price claims to verification and assurance signals, in line with Performance Expectancy exerting no significant direct effect on Behavioral Intention ($\beta = -0.033$; $p = 0.8030$) while reaching intention only through Trust (indirect $\beta = 0.103$).

The screens map to the empirical hierarchy as follows. (a) The landing page leads with price transparency, quality assurance and traceable delivery, and reports verified-supplier and delivery-service counters rather than transaction volume, reinforcing Social Influence ($\beta = 0.212$). (b) Login and registration use three-step institutional verification (document upload $\rightarrow$ procurement profile $\rightarrow$ activation) to address the Effort Expectancy barrier. (c) The buyer dashboard consolidates active orders, spending and reorder shortcuts (EE) with at-a-glance delivery status addressing the delivery-delay barrier cited by 20.9% of buyers (FC). (d) Supplier onboarding lets buyers bring existing trusted suppliers onto the platform under escrow, digital invoicing and tracking, directly addressing the most prevalent barrier — preference for established fixed suppliers (31.3%) — by digitizing relationships rather than replacing them (Trust, FC). (e) The product catalog makes verification status the dominant visual element (certification badge, minimum order quantity, live stock, supplier rating), addressing product-quality uncertainty (17.4%) and supporting Trust ($\beta = 0.235$); cross-supplier price comparison is a screening aid only, consistent with the elimination of the PE2 indicator during outer-model purification and the non-significant direct effect of Performance Expectancy. (f) Bulk order and price negotiation support volume requests, target-price submission and counter-offers against a 30-day price history, operationalizing the second-ranked feature priority ($M = 1.64$; 88.7% scoring 1–2) while preserving per-transaction flexibility. (g) A maximum four-step checkout (EE) with mandatory escrow addresses the transaction-security barrier (6.1%; Trust). (h) Real-time GPS delivery tracking addresses the delivery-delay barrier (20.9%; FC).

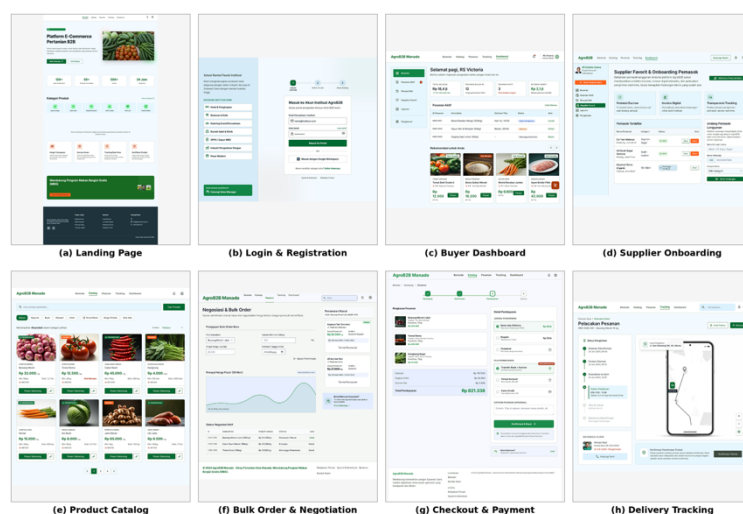


Figure 3. Mock-up: AgroB2B B2B Platform Key Screens (a) Landing Page (b) Login & Registration (c) Buyer Dashboard (d) Supplier Onboarding (e) Product Catalog (f) Bulk Order & Negotiation (g) Checkout & Payment (h) Delivery Tracking. Source: Researchers' design based on UTAUT empirical findings (2026).

The eight mock-ups collectively constitute a TRL 2 design asset ready for participatory prototype development (TRL 3–4) with institutional buyers.

3.8. Strategic Implications (RQ 4)

3.8.1. Implications Based on Adoption Determinants

3.8.1.1. Performance Expectancy as an Indirect Lever Operating Through Trust

PE reaches Behavioral Intention only indirectly (indirect $\beta = 0.103$ through Trust; BCa CI [0.029, 0.203]), its direct path being non-significant. Functional value must therefore be demonstrated in verifiable rather than promotional form: dashboards displaying audited cost savings against traditional market prices, supplier price consistency, and procurement efficiency metrics tied to actual transaction records.

3.8.1.2. Effort Expectancy and the Simplicity Challenge

EE carries the largest total effect on adoption intention (direct $\beta = 0.294$, $p = 0.0124$; total $\beta = 0.345$, $p = 0.0028$) while recording the lowest construct mean in the study (1.85). This combination makes usability the single highest-return intervention: maximum four-step ordering, institution-specific onboarding, a lightweight mobile version, and order entry through channels institutions already use.

3.8.1.3. Trust as the Foundation, not a Feature

Trust ($\beta = 0.235$; $p = 0.0201$) must be built into platform infrastructure: mandatory escrow, tiered supplier certification, and 24-hour quality refund guarantees — not optional features. Its strategic weight exceeds its coefficient, because it is the only route through which perceived performance value is converted into adoption intention.

3.8.1.4. Facilitating Conditions as Infrastructure Prerequisites

FC (direct $\beta = 0.261$, $p = 0.0323$; total $\beta = 0.291$, $p = 0.0199$) requires real-time GPS tracking, flexible delivery scheduling, and reliable local logistics partnerships. Notably, FC does not significantly predict Trust ($\beta = 0.128$; $p = 0.1465$), indicating that infrastructure availability enables adoption without in itself generating confidence in the transacting party — the two must be addressed through separate mechanisms.

3.8.1.5. Social Influence as an Ecosystem Accelerator

SI is significant both directly ($\beta = 0.212$; $p = 0.0044$) and through Trust ($\beta = 0.158$; $p = 0.0160$), giving a total effect of 0.250 ($p = 0.0007$). It is best leveraged through institutional referral programs, visible adoption counters, and a “Favorite Supplier” feature that preserves existing buyer-supplier relationships within the platform. Notably, SI shows the widest discriminant separation from all other constructs (HTMT < 0.78), making it the most empirically distinct lever available.

3.8.1.6. Relational Trust, Institution-Based Trust, and the Transition Between Them

A further implication concerns the object of trust itself. Trust is specified here as platform-oriented, yet the prominence of fixed-supplier preference as the largest barrier (31.3%) suggests buyers are not evaluating an unfamiliar platform in a relational vacuum: most already hold relational trust built through repeated transactions and physical inspection of goods. Adoption therefore requires a transition from this incumbent relational trust to institution-based trust in the platform, built through structural safeguards rather than interpersonal history. Pavlou’s (2002) five institutional mechanisms for institution-based trust in online B2B marketplaces — monitoring, legal bonds, accreditation, feedback and cooperative norms — map directly onto the architecture in Section 3.6: real-time tracking and SLA management (monitoring); escrow and dispute resolution (legal bonds); supplier certification and grading (accreditation); supplier ratings and verified delivery records (feedback); and reference pricing and grading standards via the Ecosystem Layer (cooperative norms).

This transition is temporal rather than competitive: institutional trust can substitute for familiarity and progressively complement it as the relationship matures (Pavlou, Tan, & Gefen, 2003), so the Favorite Supplier and supplier-onboarding function (Section 3.7.4) let buyers carry existing supplier relationships into the platform rather than replacing them outright. Trust-transfer evidence supports this: it occurs both within a channel (Stewart, 2003) and across channels, offline to online (Kuan & Bock, 2007) — though word-of-mouth outweighs offline trust as an input, consistent with Social Influence’s significant direct ($\beta = 0.212$) and indirect ($\beta = 0.158$) effects here. These propositions are not directly tested, since the instrument measures Trust as a single construct; future research should model incumbent relational trust and institution-based trust as distinct constructs to test the transition directly.

3.8.2. Strategic Implications by Institutional Buyer Segment

Table 16 presents segment-specific profiles and strategic implications. Because three of the six segments contain fewer than ten respondents, between-segment differences are reported descriptively and were not tested inferentially.

Table 16. Institutional Buyer Segment Profile and Strategic Platform Implications (N = 115)

Institutional Segment	n	PE	EE	BI	Specific Platform Implications & Recommendations
Modern Market	2	3.50	2.63	2.83	Standardized labeling and packaging; real-time stock data; multi-SKU management
Hotel	11	2.02	1.86	2.30	Structured delivery schedules compatible with hotel operations; guaranteed supply regularity; integration with institutional procurement systems
Hospital	11	2.41	2.16	2.03	Documented quality and food-safety certification; scheduled standing orders; compliance-ready digital invoicing

Restaurant / Cafe	82	2.12	1.81	1.92	Small-lot ordering without large minimum quantities; scheduled and same-day delivery; trust-building through trial period and physical inspection option
Catering	7	2.04	1.61	1.81	Event-based bulk ordering; firm delivery-time guarantees; quality documentation at packing
MBG Kitchen	2	1.25	1.63	1.17	Simplified interface and onboarding support; fixed reference pricing; integration with program procurement rules
Overall	115	2.14	1.85	1.96	80.9% in the low or very low interest category, 13.0% moderate and 6.1% high (none very high) — an underdeveloped market with no established high-intention segment

Note: Cell values are construct means on a five-point scale. PE = Performance Expectancy; EE = Effort Expectancy; BI = Behavioral Intention. All six segments fall below the scale midpoint of 3.00 on every construct reported. Three of the six segments contain fewer than ten respondents (Modern Market $n = 2$; MBG Kitchen $n = 2$; Catering $n = 7$), and Restaurants/Cafes account for 71.3% of the sample, so between-segment differences are descriptive only and were not tested inferentially. Platform implications are design proposals derived from the segment profiles rather than statistical findings. Source: Primary data analysis (2026).

3.8.3. Strategic Implications for Key Stakeholders

The determinant hierarchy implies distinct actions for each stakeholder. Platform developers should build an MVP (months 1–3) that prioritizes usability and facilitating infrastructure first, with trust mechanisms as the conversion layer, under a freemium-to-subscription model with a 1.5–2.5% success-based transaction commission to minimize early friction. Local government and the Department of Agriculture can create minimum viable demand by mandating institutional procurement through verified platforms — important given that only 6.1% currently express high intention — while subsidized digital training directly addresses the lowest-scoring construct (Effort Expectancy, $M = 1.85$). Farmers and suppliers require packaging standardization, grading training and SLA commitment, with agricultural cooperatives serving as collective aggregators to address smallholder scale. For investors, the model's explanatory power ($R^2 = 0.653$ for Behavioral Intention; $R^2 = 0.669$ for Trust) coexists with a weak demand signal (80.9% low or very low; 13.0% moderate; 6.1% high), so investment cases should rest on market development, with earliest monetization in the small high- and moderate-intention groups. Priority research agendas are: (1) UAT prototype testing targeting >70% acceptance (TRL 3–4); (2) replication across Eastern Indonesian cities (Makassar, Ambon, Jayapura); and (3) integration of supplier perspectives into an upstream–downstream framework.

3.8.4. National Policy Implications

Four policy recommendations align with SDGs 2 and 9, Presidential Asta Cita No. 2 and 6, and RPJMN 2025–2029. First, integrate B2B agricultural e-commerce into the Free Nutritious Meals (MBG) program by mandating raw-material procurement through verified platforms with subsidy and training, advancing digital procurement and guaranteeing market access for local farmers. Second, accelerate digital and logistics infrastructure in production centres within the Kementan and Kominfo digital-agriculture roadmap, prioritizing the delivery reliability the model identifies as a significant determinant. Third, standardize agricultural grading and certification calibrated to each buyer type, since hospital standards differ from restaurant standards. Fourth, use this research model as a national replication blueprint for adoption studies in other Indonesian cities with similar logistical and institutional characteristics.

3.8.5. Strategic Implications Synthesis

All strategic implications converge on a single point: success in B2B agricultural e-commerce depends less on technological sophistication than on whether the platform can substitute credibly for the supplier relationships institutional buyers currently trust. With 80.9% of buyers expressing low or very low intent and only 6.1% high intent, the market must be built before it can be broadened, and the empirical hierarchy sets a clear development order — remove interface friction first (EE total $\beta = 0.345$), then secure facilitating infrastructure (FC total $\beta = 0.291$), then build trust as the conversion layer (Trust $\beta = 0.235$), since Trust is the sole channel through which perceived performance value reaches adoption intention. These priorities are developed in full in the Conclusion.

4. CONCLUSION

Institutional buyers in Manado City demonstrate predominantly low adoption intention toward B2B agricultural e-commerce (mean BI = 1.96, SD = 0.75; 80.9% low or very low, 13.0% moderate, 6.1% high), so the market is underdeveloped rather than simply untapped. PLS-SEM with 5,000 bootstrap subsamples supported seven of nine hypotheses ($R^2 = 0.653$ for Behavioral Intention; $R^2 = 0.669$ for Trust; SRMR = 0.0885). Ranked by total effect, the determinants are Effort Expectancy ($\beta = 0.345$; $p = 0.0028$), Facilitating

Conditions ($\beta = 0.291$; $p = 0.0199$), Social Influence ($\beta = 0.250$; $p = 0.0007$) and Trust ($\beta = 0.235$; $p = 0.0201$); Performance Expectancy influenced intention only indirectly through Trust (indirect $\beta = 0.103$; BCa CI [0.029, 0.203]; $p = 0.0189$), its direct path non-significant and total effect negligible ($\beta = 0.070$; $p = 0.5787$).

The results depart from the original UTAUT in two respects. Performance Expectancy — the strongest predictor in Venkatesh et al. (2003) — exerts no direct effect, operating entirely through Trust: in a pre-adoption population, belief in functional benefit converts into intention only once anchored in confidence in the transacting party, consistent with the initial-trust literature (Gefen et al., 2003; Pavlou, 2003). And Facilitating Conditions predicts intention rather than only usage, reflecting a context where delivery reliability and resource readiness are prerequisites. The remaining relationships are consistent with UTAUT, so the contribution is not a rejection of UTAUT but the identification of Trust as the mediating mechanism through which Performance Expectancy operates in institutional B2B procurement.

Several limitations apply. First, discriminant validity holds only with narrow margins: Fornell-Larcker is satisfied for all six constructs and no HTMT pair exceeds 0.85, though three Performance Expectancy pairings sit immediately below it (0.8482–0.8489); within-construct correlations (0.470–0.617) exceed between-construct ones (mean 0.420) and Harman's single-factor test returns 48.8% of variance, so constructs are not undifferentiated — the high HTMT values more plausibly reflect the pronounced floor effect. Because the separation between Performance Expectancy and Trust is the narrowest of these, the central finding that Performance Expectancy operates through full mediation by Trust should be read as provisional: it is consistent with the data but cannot be sharply distinguished from the two constructs sharing substantial common variance, and requires confirmation with an instrument that separates them more cleanly. Second, Social Influence is measured by only two retained indicators after outer-model purification, so its reliability estimates and the significant SI paths should be interpreted with corresponding caution. Third, statistical power at $n = 115$ means the two non-significant paths are undetected rather than shown absent. Fourth, the single-city sample — dominated by restaurants/cafes (71.3%) and with compressed response variance — limits both cross-segment and geographic generalization and the precision of the estimates. Results are therefore exploratory and require replication in a more heterogeneous setting.

Conceptual Model and Platform Design. The study formulates a demand-driven conceptual model around five dimensions — Usability (EE), Logistics & System Support (FC), Digital Trust (TR), Functional Value (PE) and Social Network & Community (SI) — operationalized through a six-layer architecture. As a TRL 2 output, eight evidence-based mock-up screens (Figure 3), each traceable to specific findings, constitute a ready design asset for interactive prototype development (TRL 3–4) through participatory design with institutional buyers.

Strategic Implications and Research Contributions. Three MVP priorities emerge from the determinant hierarchy, in an order that inverts conventional agritech practice: (1) remove interface friction first (EE total $\beta = 0.345$ — four-step ordering, institution-specific onboarding, lightweight mobile access); (2) secure institutional resource readiness (FC total $\beta = 0.291$ — delivery reliability, technical assistance, designs matched to daily high-volume purchasing); and (3) build trust as infrastructure rather than an optional feature (Trust $\beta = 0.235$ — mandatory escrow, supplier certification, quality guarantees), which is also the sole conduit for Performance Expectancy (indirect $\beta = 0.103$). Functional richness and headline pricing, which conventional practice addresses first, correspond to no construct that predicts intention here.

Theoretically, the study contributes: (i) the first demand-driven quantitative evidence of B2B agricultural e-commerce adoption from Eastern Indonesia; (ii) evidence that Trust functions as a mediator rather than a parallel determinant, with Performance Expectancy operating entirely through it; (iii) a demand-driven conceptual model and six-layer architecture translating the determinant hierarchy into a TRL 2 design asset for a pre-adoption market; and (iv) a specification of adoption in incumbent-dominated markets as a transition between relational trust in known suppliers and institution-based trust in the platform. Future research should diversify the sample across cities and institution types, sharpen discriminant separation between Performance Expectancy and Trust, and test the model with respondents who have actual platform experience.

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