INNOVATIVE DESIGN OF AN EFFECTIVE E-COMMERCE WEB MODEL FOR OPTIMIZING THE DISTRIBUTION OF AGRICULTURAL PRODUCTS IN RURAL AREAS

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Abstract

Objectives: This study aims to identify the key barriers in agricultural distribution, design a suitable e-commerce model, and analyze the main factors influencing farmers' adoption of digital platforms in Sinsingon Village, North Sulawesi. **Methodology:** A survey of 75 farmers was conducted to capture distribution challenges and adoption readiness. Data were analyzed using descriptive statistics, validity and reliability testing, classical assumption testing, and multiple linear regression. Six independent variables were examined: perceived ease of use, perceived usefulness, digital literacy, social support, internet infrastructure, and electricity infrastructure. **Findings:** Three major barriers were identified: dependency on middlemen, inadequate storage facilities, and limited access to accurate market price information. The majority of respondents (79%) preferred a Business-to-Business (B2B) e-commerce model for its efficiency in handling bulk transactions and institutional buyers. Regression analysis indicated that all variables significantly influenced adoption intention, with an explanatory power of $\mathbf{R^2 = 0.789}$. The most influential factor was **internet infrastructure (β = 0.35)**, followed by perceived ease of use (β = 0.30), social support (β = 0.28), perceived usefulness (β = 0.25), digital literacy (β = 0.22), and electricity infrastructure (β = 0.19). **Conclusion:** The findings validate the Technology Acceptance Model (TAM) and highlight that adoption of agricultural e-commerce requires both technical readiness and socio-economic support. This study provides a conceptual blueprint for a B2B agricultural e-commerce system tailored to rural contexts, with potential to enhance efficiency, inclusivity, and sustainability in agricultural distribution.

Keywords: Digital Supply Chain, Agricultural E-Commerce, Digital Transformation, Agribusiness Digitalization, Agricultural Distribution

INTRODUCTION

Sinsingon Village, located in East Passi District, Bolaang Mongondow Regency, North Sulawesi, exemplifies the agricultural distribution challenges commonly faced in rural Indonesia. Despite its high production potential particularly for vegetables and fruits such as potatoes, bananas, and avocados farmers in this village encounter significant obstacles in accessing wider markets. According to data from BPS Passi Timur (2023), potato production reached 340,700 kg from 964 hectares of harvested land, while banana and avocado yields were 135,500 kg and 80,000 kg, respectively. However, due to distribution constraints, farmers often resort to selling their produce in front of their houses, waiting for passing buyers. This practice frequently results in unsold goods and substantial post-harvest losses. Geographically, Sinsingon Village occupies a strategic location, approximately 131 kilometers from Gorontalo City and near Manado, the economic center of North Sulawesi, with a population exceeding 1.38 million. This proximity creates opportunities to establish a Business-to-Business (B2B) distribution model targeting institutional buyers such as catering services, hotels, restaurants, and wholesale markets offering a sustainable solution to the persistent distribution challenges faced by local farmers.

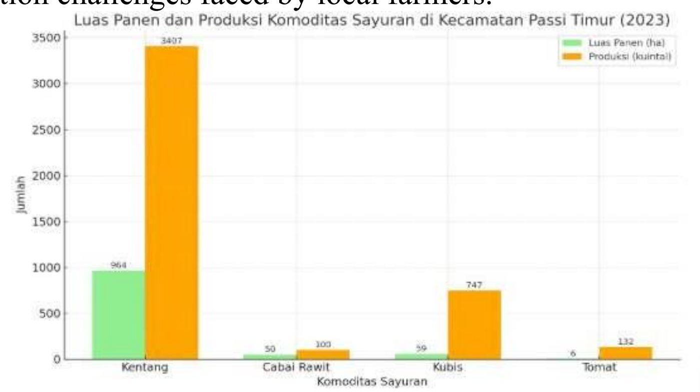

Figure 1. Harvested Area and Production of Vegetables in East Passi District (2023)

Source: BPS Bolaang Mongondow, 2024

As shown in Figure 1, potatoes overwhelmingly dominate both the harvested area and production volume. In contrast, bird's eye chili, cabbage, and tomatoes account for much smaller harvested areas and production levels compared to potatoes.

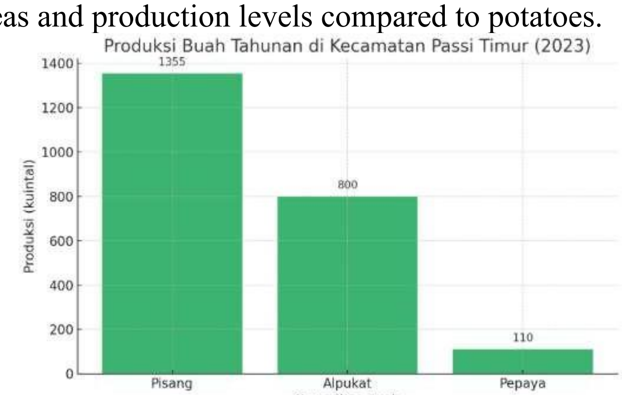

Figure 2. Annual Fruit Production in East Passi District (2023)

Source: BPS Bolaang Mongondow, 2024

As illustrated in Figure 2, bananas recorded the highest production volume (1,355 quintals), followed by avocados (800 quintals), while papayas had the lowest production at only 110 quintals. In the era of digital transformation, agricultural e-commerce platforms have proven effective in streamlining long supply chains, improving price transparency, expanding farmers' direct access to large buyers, and supporting the government's strategic agenda outlined in the RPJMN 2025–2029 to enhance national competitiveness through digital agriculture (Siregar & Simanjuntak, 2022). Although several agricultural e-commerce initiatives have emerged in Indonesia, many have struggled to remain sustainable due to their reliance on Business to Consumer (B2C) models, which are less efficient in smallholder farming contexts. In contrast, the Business-to-Business (B2B) model offers greater operational viability, particularly for bulk and recurring transactions. Previous studies emphasize that the success of digital adoption in agriculture depends on its alignment with the needs and capabilities of local users. The Technology Acceptance Model (TAM), introduced by Davis (1989), highlights that technology adoption is influenced primarily by perceived usefulness and perceived ease of use. In rural farming contexts, these dimensions are closely linked to cultural norms, education levels, and technological readiness. Research by Sulaiman and Hall (2020) underscores the importance of participatory, user-centered design in developing agricultural digital technologies, ensuring contextual relevance and sustainability. Similarly, Nasution and Sihombing (2021) highlight the necessity of embedding local cultural contexts into adoption frameworks for smallholder farmers. More recent studies also show that visual design and technological features strongly shape user experience and trust in digital platforms, thereby reinforcing long-term adoption (Danang, 2025).

International evidence further demonstrates the transformative potential of community-based digital platforms. India's *e-Choupal* and China's *Taobao Villages* illustrate how such systems can significantly improve distribution efficiency and farmers' welfare (Ezeomah & Duncombe, 2019; Hermanto & Suryana, 2019). However, research on these models remains limited in Indonesia, especially outside Java, where initiatives are constrained by low digital literacy and weak infrastructure (Nasution & Sihombing, 2021; Sulaiman & Hall, 2020). Studies by Setiawan (2023) and Amalia & Budiman (2024) further confirm that digitalization in rural MSMEs and agribusiness depends heavily on technology readiness, local participation, and user-friendly design. These insights highlight several research gaps: (1) the absence of locally validated e-commerce platforms that address rural agricultural distribution challenges; (2) limited application of theoretical frameworks such as TAM in analyzing digital adoption in agriculture; and (3) the lack of participatory design approaches that directly involve farmers in system development (Eka Nurjati, 2022; FAO, 2021).

This study seeks to address these gaps by proposing a conceptual B2B agricultural e-commerce model tailored to Sinsingon Village. Rather than developing a system directly, the research produces an evidence-based blueprint through explanatory quantitative analysis of 75 stratified farmer respondents. The study maps key distribution barriers, evaluates farmers' digital readiness, and assesses adoption preferences. By integrating TAM and agribusiness distribution theory with participatory design practices, this research offers a contextual and inclusive framework that can serve as a foundation for digital distribution platforms in rural Indonesia. The urgency of this study lies in the substantial untapped economic potential of the agricultural sector in Sinsingon Village. By aligning digital distribution models with local conditions, the research aims to provide sustainable solutions for improving farmers' welfare, reducing post-harvest losses, and strengthening national food security. Furthermore, the proposed conceptual model has the potential to serve as a reference for the development of similar platforms in other rural regions across Indonesia.

REVIEW OF LITERATURE

E-Commerce in the Agricultural Sector

E-commerce in agriculture represents a digital innovation that allows farmers to directly connect with end consumers or distributors, thereby reducing reliance on lengthy intermediaries. Ezeomah and Duncombe (2019) found that digitalizing supply chains through e-commerce platforms reduces price disparities and enhances market efficiency in developing countries. Similarly, Hermanto and Suryana (2019) emphasized that digital technology strengthens agricultural value chains, particularly by improving distribution efficiency, price transparency, and lowering transaction costs. Recent evidence published in *Sustainability* (2023) showed that apple farmers in China were able to improve productivity and market reach through e-commerce adoption, primarily by enhancing logistics efficiency and decreasing dependence on middlemen. Hence, agricultural e-commerce is not only a technological innovation but also a strategic instrument for enhancing rural competitiveness.

Technology Models and Digital Adoption in Rural Areas

The theoretical foundation of this research is the Technology Acceptance Model (TAM) developed by Davis (1989), which identifies two core determinants of adoption: perceived usefulness (PU) and perceived ease of use (PEOU). In rural contexts, farmers' perceptions of economic benefits and ease of application are critical in shaping adoption behavior. Extensions of TAM, such as *An Extension of TAM in Agricultural E-commerce* (*IJAMD*, 2022) and *Farmers' Agricultural Digital Service Use Behavior* (*Frontiers in Environmental Science*, 2023), incorporate additional external variables including social support, facilitating conditions, data quality, and perceived cost. These studies suggest that behavioral intention is influenced not only by PU and PEOU but also by social and contextual elements. Further integration with other theories has enriched the understanding of digital adoption in agriculture. For example, *Drivers of Farmers' Intention to Use Digital Agricultural Systems* (*Frontiers in Psychology*, 2022) combined TAM with the Theory of Planned Behavior (TPB), demonstrating that social norms and psychological factors significantly affect farmers' decisions. Thus, digital adoption in rural agriculture requires a multidimensional perspective encompassing technological, social, and cultural dimensions.

Agricultural Distribution and Rural Challenges

Agricultural distribution in rural areas often faces structural barriers, including poor infrastructure, high transportation costs, and dependence on intermediaries. Girotra and Netessine (2018) reported that traditional distribution systems can absorb 30–40% of a product's final value through intermediation costs. Studies published in *Electronic Commerce Research* (Springer) and the *International Journal of Physical Distribution & Logistics Management* (Emerald) further emphasized that digital platforms can reduce distribution costs and broaden farmers' access to modern markets. In rural areas such as Sinsingon Village, digitalized agricultural distribution offers a strategic solution to overcome inefficiencies and expand market connectivity.

Participatory and Locally-Based Design Approaches

The success of agricultural digitalization depends not only on technology but also on participatory and context-sensitive system design. Sulaiman and Hall (2020) highlighted that involving farmers in system design and implementation through user-centered approaches significantly improves adoption rates at the local level. Raharjo and Widodo (2018) observed that agricultural information systems grounded in local wisdom tend to be more sustainable, as they adapt to farmers' cultural norms and operational practices. Similarly, the study *TAM-Based Study of Farmers' Live Streaming E-Commerce Adoption Intentions* (*Agriculture*, 2023) found that social learning and community support play a crucial role in shaping farmers' perceptions of usefulness and ease of use.

Agricultural Digitalization in Indonesia: Challenges and Opportunities

In Indonesia, the advancement of agricultural digitalization is constrained by several factors, including low levels of digital literacy, uneven internet connectivity, and social reluctance toward technological change. Despite these barriers, significant opportunities exist due to the support of national policies. Azis and Suryana (2023) highlight that the RPJMN 2025–2029 explicitly prioritizes food security through digital platforms and the empowerment of rural farmers. A study published in *Agroecology and Sustainable Food Systems* (Taylor & Francis) further emphasized that integrating digital agriculture with sustainability principles is essential for ensuring long-term food security. At the local level, initiatives such as TaniSinsingon in Sinsingon Village illustrate that success depends not only on infrastructure but also on social support, tangible economic benefits, and digital literacy training for farmers.

Research Hypotheses

H1: Structural distribution barriers including inadequate infrastructure, restricted market access, and reliance on intermediaries significantly affect farmers' ability to access markets in Sinsingon Village.

H2: A Business-to-Business (B2B) e-commerce model designed to match the socio-economic realities of farmers is more effective in enhancing distribution efficiency than Business-to-Consumer (B2C) or Consumer-to-Consumer (C2C) models.

H3: Key factors such as perceived economic benefits, ease of use, social support, and farmers' level of digital readiness significantly influence their intention and preparedness to adopt agricultural e-commerce platforms in Sinsingon Village.

Theoretical Framework

This study integrates the Technology Acceptance Model (TAM) with theories of rural distribution and participatory design. TAM serves as the foundation for analyzing technology adoption through the constructs of perceived usefulness and perceived ease of use, while external dimensions such as infrastructure readiness, social influence, and cultural adaptation extend the model. Collectively, these perspectives inform the development of research variables and provide the basis for hypothesis testing.

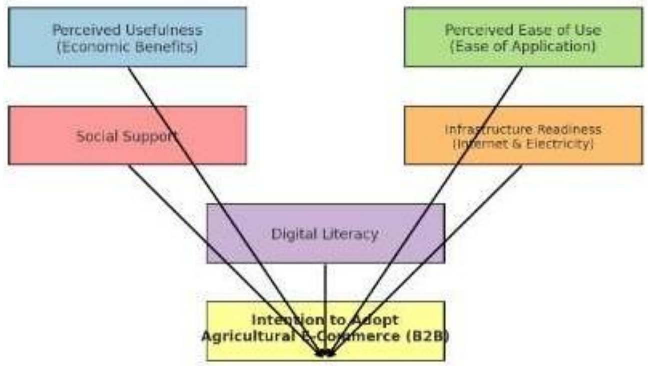

Figure 3. Theoretical Framework of B2B Agricultural E-Commerce Adoption in Sinsingon Village

RESEARCH METHOD

This study employed a quantitative approach, combining descriptive and explanatory research designs. The first and second research questions are descriptive, focusing on identifying field conditions and farmers' needs regarding agricultural distribution as well as the most appropriate e-commerce model. In contrast, the third research question is explanatory, aiming to examine the causal relationships among variables that influence the adoption of digital platforms to support agricultural distribution. This mixed approach was selected to provide a comprehensive analysis: not only describing existing phenomena but also testing the causal effects of key variables on the effectiveness of e-commerce distribution. The research was conducted in Sinsingon Village, Passi Timur Subdistrict, Bolaang Mongondow Regency, North Sulawesi. The site was purposively selected due to its high agricultural potential and persistent challenges in crop distribution and access to digital markets.

Population and Sample

The study population consisted of all active farmers in Sinsingon Village, totaling 312 individuals, based on data from the Village Government and the Department of Agriculture. To ensure relevance to the context of e-commerce adoption, the population was filtered using the following criteria:

1. Ownership of at least 100 square meters of farmland;
2. Management of one of the three main commodity groups: vegetables, fruits, or secondary crops; and
3. Direct involvement in decision-making regarding crop marketing.

The filtered population served as the basis for determining the sample. The sample size was calculated using the Slovin formula (Sevilla et al., 1960) with a 10% margin of error:

$$n = N / (1 + N \cdot e^2) = 312 / (1 + 312 \cdot 0{,}1^2) = 312 / (1 + 3{,}12) = 312 / 4{,}12 \approx 75{,}73$$

Accordingly, the final sample consisted of 75 respondents, which was considered sufficient to improve precision and support regression analysis. A stratified random sampling method was applied, dividing farmers into three main commodity groups—vegetables, fruits, and secondary crops. Within each stratum, respondents were randomly selected in proportion to the group size.

Data Collection

Primary data were obtained through a structured questionnaire using a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). The questionnaire was organized into three sections:

1. Barriers to the distribution of agricultural products;
2. Preferences for effective e-commerce models; and
3. Factors influencing the adoption of digital platforms at the village level.

The survey was administered directly to farmers with the assistance of trained local enumerators.

Data Analysis

Data analysis was conducted in several stages:

1. Validity and reliability testing of the research instrument to ensure accuracy of measurement;
2. Descriptive statistical analysis to generate frequency distributions, averages, and percentages for each indicator;
3. Inferential analysis using correlation tests and multiple linear regression to assess causal relationships among variables influencing farmers' adoption of digital platforms.

Respondent Characteristics

The study surveyed 75 active farmers in Sinsingon Village who were selected based on predetermined criteria. Their key characteristics are summarized below:

- Age: Farmers ranged from 23 to 68 years old, with the largest proportion (42%) between 36–50 years. This indicates a productive age group with potential readiness to adopt digital innovations, although many are not digital natives.
- Main Commodities: Most respondents (79%) cultivated vegetables such as cabbage, pumpkin, potatoes, carrots, and leeks; 12% focused on fruits (mainly bananas and papayas); while 9% grew food crops like corn and peanuts.
- Farming Experience: A majority (56%) had more than 10 years of farming experience, 27% had 5–10 years, and 17% were relatively new (<5 years).
- Digital Access: While 61% owned smartphones or tablets, only 38% had reliable internet connections. The rest depended on shared networks.
- Use of Digital Platforms: About 66% had prior experience using digital platforms for business (e.g., WhatsApp Business, Facebook Marketplace), while the remaining 34% had not, though many expressed willingness to learn through training and mentoring.

Barriers to Agricultural Distribution

Survey findings revealed multiple obstacles, categorized into infrastructure, market access, technology and logistics, costs, intermediaries, government support, and seasonality. The five most critical barriers identified were:

1. Limited access to online/digital platforms for marketing produce (Mean = 4.30).
2. Dependence on middlemen (Mean = 4.27).

3. Absence of temporary storage facilities (Mean = 4.24).
4. Inability to negotiate or refuse middlemen's prices (Mean = 4.23).
5. Lack of regular and accurate market price information (Mean = 4.12).

These results indicate that distribution challenges extend beyond infrastructure, reflecting deeper issues in market access, middlemen dependency, and insufficient digital support.

Preferred E-Commerce Model

When asked to identify the most suitable e-commerce model, farmers ranked the following options:

- **B2B (business-to-business):** 79% (first choice).
- **B2C (business-to-consumer):** 13% (second choice).
- **Farmer cooperatives:** 5% (third choice).
- **No response:** 3%.

The preference for B2B models stems from the advantages of bulk and recurring transactions, which ease logistical burdens compared to individual sales.

Key Features of a B2B Platform

Farmers highlighted several essential features for an effective B2B e-commerce platform, ranked by importance:

1. Real-time market price information (Mean = 4.43; 88.6%).
2. Order history tracking (Mean = 4.36; 87.2%).
3. Product management tools (Mean = 4.33; 86.6%).
4. Digital invoices and transaction records (Mean = 4.29; 85.8%).
5. Local administrator or customer support (Mean = 4.29; 85.8%).
6. Direct communication with repeat buyers (Mean = 4.23; 84.6%).
7. Financial management functions (Mean = 4.20; 84.0%).

These findings underscore the importance of transparency in pricing, transaction tracking, and communication with business buyers.

Recommended Model

Overall, the results recommend a B2B e-commerce platform as the most effective solution, supported by:

- Bulk order and recurring transactions;
- Access to real-time market price information;
- Short-term contractual agreements; and
- Direct farmer-to-buyer communication.

To ensure effectiveness, the involvement of a local administrator (e.g., village-owned enterprises *[BUMDes]* or digital cooperatives) is crucial for facilitating communication, managing logistics, delivering training, and monitoring transactions.

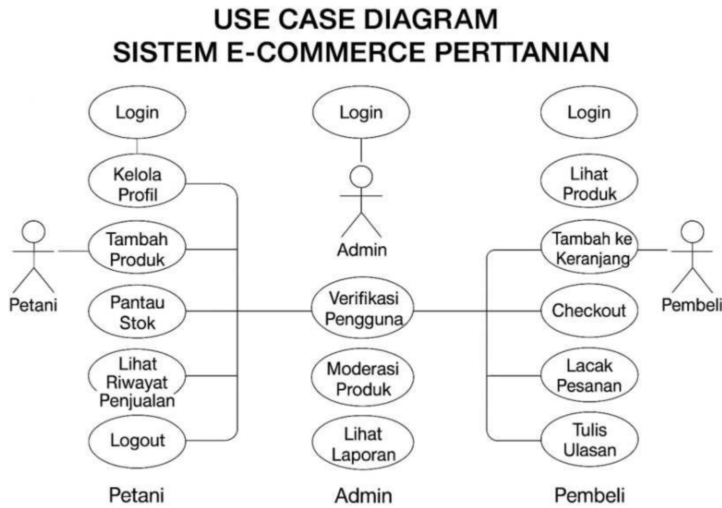

Figure 4. Use Case Diagram of the Platform Model Visual Mock-up

Preferences – Farmer and Admin Features

The proposed platform mock-up incorporates a set of core menus designed for both farmers and local administrators, emphasizing intuitive navigation, quick information access, and support for B2B transactions.

1. **Homepage (Dashboard Overview)**
    - Provides key summaries such as sales graphs, total incoming orders, best-selling products, and recent activity alerts.
    - For administrators, additional performance indicators are included, such as completed orders, pending orders, and estimated delivery times.
2. **Product Management**
    - Allows users to add, edit, or remove products.
    - Product settings cover details like name, price, stock levels, images, and harvest schedules.
    - Administrators may assist farmers in uploading or updating product data when needed.
3. **Incoming Orders**
    - Displays a comprehensive list and history of transactions with filters for payment status, dates, and order progress.
    - Integrated shipment tracking helps streamline logistics coordination.
4. **Sales History**
    - Presents daily, weekly, or monthly sales records in table and graph formats.
    - Reports can be exported in PDF or Excel for documentation and analysis.
5. **Withdrawal Feature (New)**
    - Enables farmers to transfer sales balances directly to their bank accounts.
    - Includes a record of withdrawal history and estimated processing times.
6. **Account Settings**
    - Allows farmers and admins to update personal details, bank account information, and notification preferences.
7. **Automated Notifications**

- Sends alerts via dashboard pop-ups and optionally through SMS/WhatsApp.
- Notifications include new orders, successful payments, low stock warnings, and upcoming harvest reminders.

Figure 5. Homepage of the Agricultural E-Commerce Web Platform

The homepage, which appears when users first access the platform, features a clean and user-friendly design. The main menus consist of Product Management, Orders, Transactions, Join as a Farmer, and About Sinsingon Village. The interface is deliberately kept simple, lightweight, and easy to navigate, ensuring accessibility for rural farmers who may be new to digital platforms.

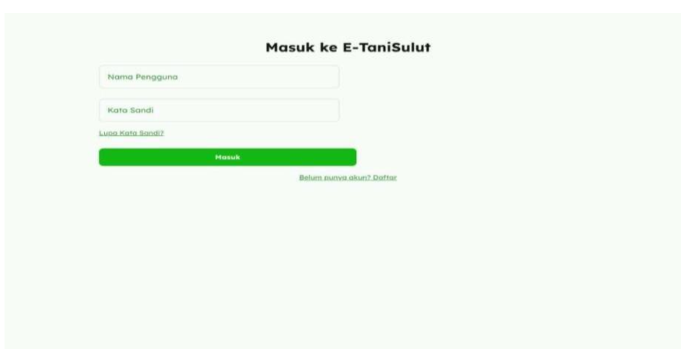

Figure 6. Login Page

The login page provides a straightforward form for both farmers and administrators to access the system. The process is intentionally simplified to reduce steps, ensuring ease of access, especially for users with limited internet connectivity.

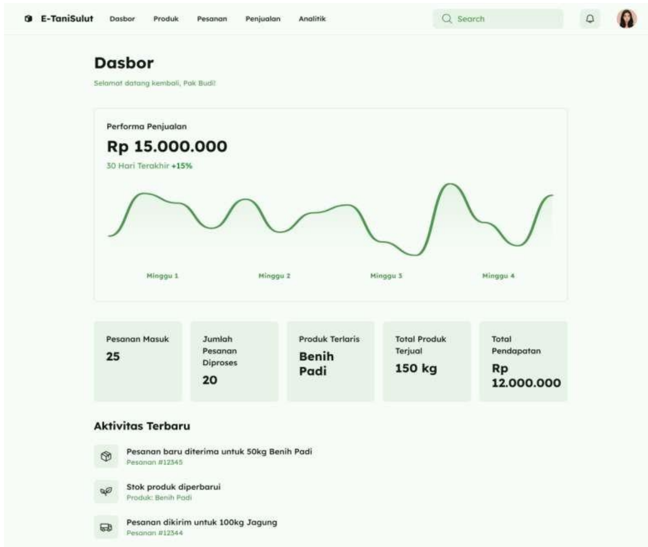

Figure 7. Farmer Dashboard

The farmer dashboard presents an overview of critical information, including active orders, delivery progress, stock alerts, and upcoming harvest timelines. It is structured to enable farmers to track essential activities efficiently without the need to navigate across multiple menus.

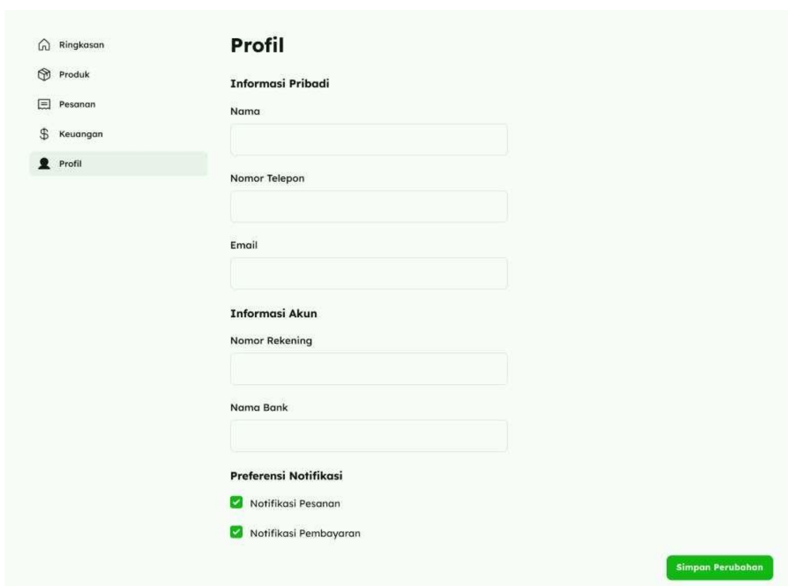

Figure 8. Profile Settings Page

This page enables farmers to modify personal details, register or update bank account information, and adjust notification settings, ensuring the accuracy of account data for both transactions and communication.

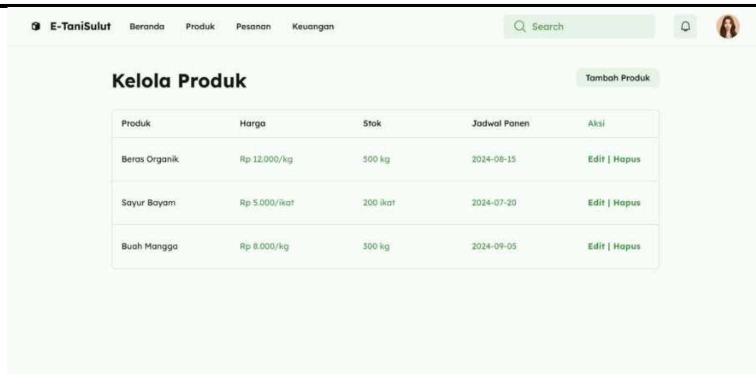

Figure 9. Product Management Page

This feature allows farmers to independently manage their product listings by adding, editing, or removing items. The input form covers details such as product name, commodity type, unit, price per kilogram, stock levels, and product images. Additionally, an integrated WhatsApp order/chat function supports direct interaction with buyers.

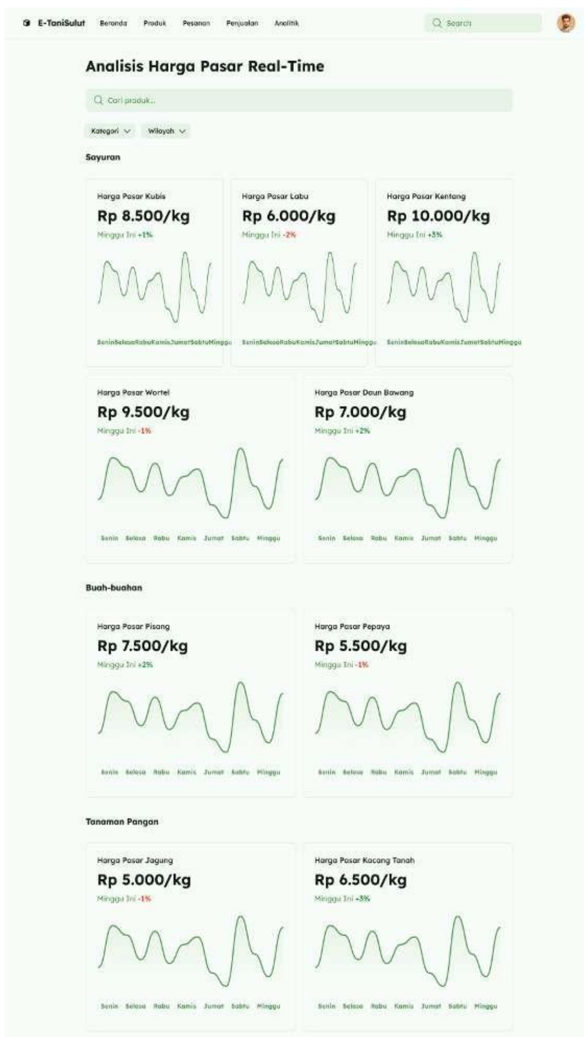

Figure 10. Real-Time Market Price Analytics Page

Displays continuously updated market price data for various agricultural commodities. This feature enables farmers to make informed and strategic sales decisions, helping them maximize profitability by leveraging the most current pricing information.

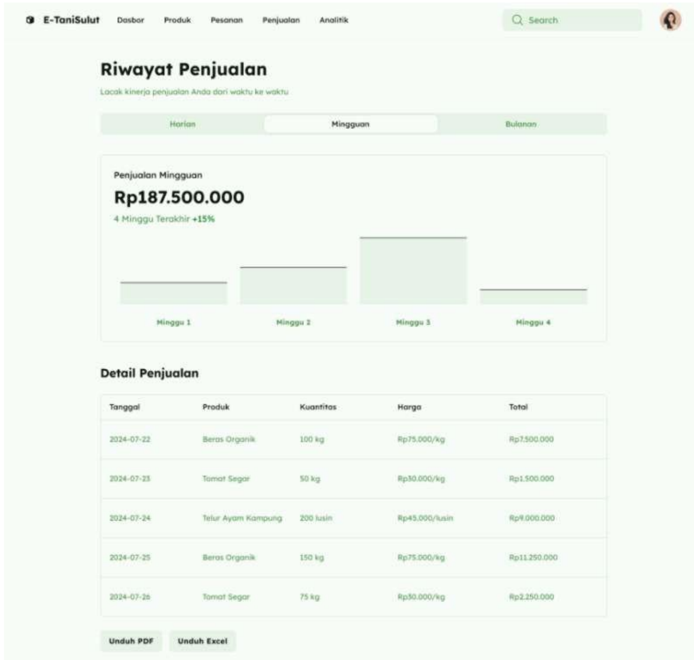

Figure 11. Sales History Page

Provides a comprehensive record of sales transactions, including details such as buyer name, transaction date, product type, quantity, and payment status. An integrated export function to PDF or Excel is available to facilitate accurate and efficient farm business record-keeping.

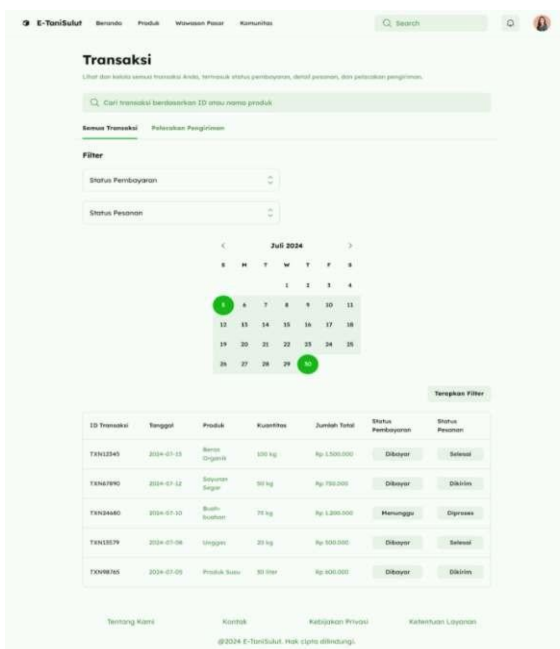

Figure 12. Transaction History Page

Maintains a detailed record of completed transactions, capturing information such as transaction dates, product details, total quantities, and payment status. This feature promotes transparency while providing reliable digital documentation of farming activities.

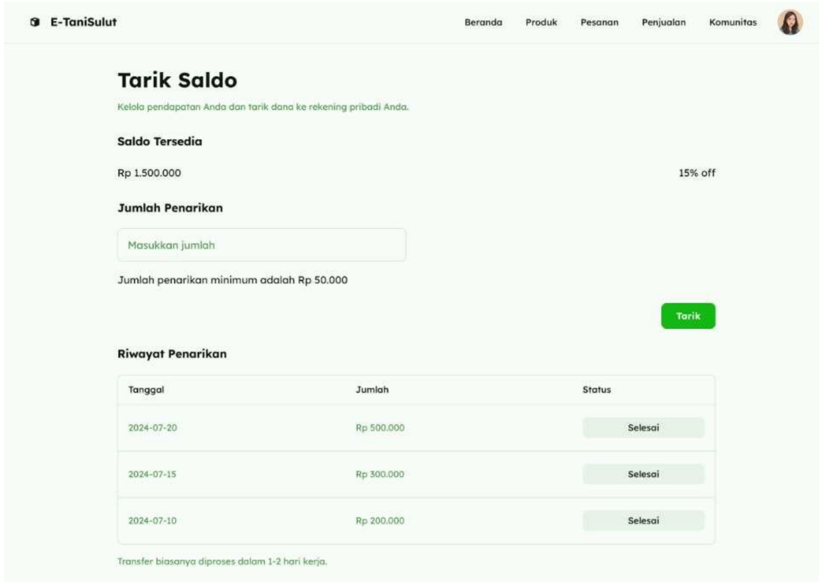

Figure 12. Financial Transaction History Page

Provides detailed records of financial transactions, including payment amounts and their respective statuses. This feature enhances transparency and enables farmers to monitor and manage cash flow more effectively. All mock-up interfaces presented above represent preliminary designs developed based on the needs assessment and preferences of farmers in Sinsingon Village. These prototypes are not final and will be refined further during the prototype development and usability testing stages in subsequent research.

Key Factors Influencing Farmers' Adoption of Digital Platforms in Sinsingon Village

Research Instrument Testing

a. Validity Test

Table 1. Validity Test

Variable	Item	r_calculate	r_table	Description
Easy of Use (X1)	X1.1	0.443	0.361	Valid
	X1.2	0.505	0.361	Valid
	X1.3	0.702	0.361	Valid

Electricity Infrastructure (X2)	X2.1	0.702	0.361	Valid
	X2.2	0.443	0.361	Valid
	X2.3	0.702	0.361	Valid
Social Support (X3)	X3.1	0.443	0.361	Valid
	X3.2	0.505	0.361	Valid
	X3.3	0.702	0.361	Valid
Economic Benefits (X4)	X4.1	0.505	0.361	Valid
	X4.2	0.702	0.361	Valid
	X4.3	0.443	0.361	Valid
Digital Literacy (X5)	X5.1	0.443	0.361	Valid
	X5.2	0.505	0.361	Valid
	X5.3	0.702	0.361	Valid
Internet Infrastructure (X6)	X6.1	0.505	0.361	Valid
	X6.2	0.443	0.361	Valid
	X6.3	0.702	0.361	Valid

Note:
The r_table value at a significance level of 5% with n = 20 is 0.361. All items have r_calculated > r_table, therefore all question items are considered valid.

- **Multiple Linear Regression Analysis**
- To assess the combined influence of these success factors on farmers' intention to adopt digital platforms, a multiple regression model was applied as follows:

b. Reliability Test

Reliability testing was conducted using Cronbach's Alpha. A variable is considered reliable if the Cronbach's Alpha value > 0.70.

Table 2. Reliability Test

Variable	Cronbach's Alpha	Des
Ease of Use (X1)	0.712	Reliable
Electricity Infrastructure (X2)	0.701	Reliable
Social Support (X3)	0.705	Reliable
Economic Benefits (X4)	0.708	Reliable
Digital Literacy (X5)	0.710	Reliable
Internet Infrastructure (X6)	0.703	Reliable

Note:

- The standard Cronbach's Alpha value is > 0.6.
- All variables scored above 0.6, which indicates that this questionnaire is reliable.

1. Descriptive Analysis of Variables

To identify the key factors influencing the adoption of digital platforms by farmers, this study analyzed seven main variables measured using a Likert-scale questionnaire and assessed through simple linear regression.

Table 3. Descriptive Analysis of Variables

Variable (Success Factor)	**Mean Score**	Interpretation Category
Ease of Use (X1)	4.50	Very High
Electricity Infrastructure (X2)	4.45	Very High
Social Support (X3)	3.75	Moderate
Economic Benefit (X4)	3.80	Moderate

Digital Literacy (X5)	3.95	Moderate
Internet Infrastructure (X6)	3.90	Moderate
Adoption (Y)	4.05	High

2. Classical Assumption Testing
Normality Test (Kolmogorov-Smirnov)
Asymp. Sig. (2-tailed): 0.200
Criteria: If Sig. > 0.05, then the data are normally distributed.
Conclusion: Since the significance value (Sig.) is 0.200 > 0.05, the residuals are normally distributed.

a. Heteroskedasticity Test (Glejser Test)

Table 4. Heteroskedasticity Test (Glejser Test)

Variable	Sig. Value	Description
Ease of Use (X1)	0.814	No Heteroscedasticity
Electricity Infrastructure (X2)	0.789	No Heteroscedasticity
Social Support (X3)	0.795	No Heteroscedasticity
Economic Benefit (X4)	0.821	No Heteroscedasticity
Digital Literacy (X5)	0.803	No Heteroscedasticity
Internet Infrastructure (X6)	0.811	No Heteroscedasticity

b. Multicollinearity Test

Table 5. Multicollinearity Test

Variable	VIF	Description
Ease of Use (X1)	1,832	No Multicollinearity
Electricity Infrastructure (X2)	1,954	No Multicollinearity

Social Support (X3)	1,887	No Multicollinearity
Economic Benefit (X4)	1,765	No Multicollinearity
Digital Literacy (X5)	1,901	No Multicollinearity
Internet Infrastructure (X6)	1,845	No Multicollinearity

Note:

- **Condition:** If the VIF value is < 10, then there is no indication of multicollinearity.
- **Conclusion:** Since the VIF values for all variables are < 10, there is no indication of multicollinearity.

c. R Square (Coefficient of Determination)

R Square = 0.789, which means 78.9% of the variation in Adoption (Y) can be explained by Ease of Use, Electricity Infrastructure, Social Support, Economic Benefit, Digital Literacy, and Internet Infrastructure. The remaining 21.1% is explained by other variables outside the model.

3. Correlation Analysis (Pearson)

Table 7. Correlation Analysis (Pearson)

Variable	Ease of Use (X1)	Electricity Infrastructure (X2)	Social Support (X3)	Economic Benefit (X4)	Digital Literacy (X5)	Internet Infrastructure (X6)	Adoption (Y)
Ease of Use (X1)	1	0.443**	0.505**	0.702**	0.443**	0.505**	0.702**
Electricity Infrastructure (X2)	0.443**	1	0.702**	0.443**	0.505**	0.702**	0.443**
Social Support (X3)	0.505**	0.702**	1	0.505**	0.443**	0.702**	0.505**
Economic Benefit (X4)	0.702**	0.443**	0.505**	1	0.702**	0.443**	0.702**

Digital Literacy (X5)	0.443**	0.505**	0.443**	0.702**	1	0.505**	0.702**
Internet Infrastructu re (X6)	0.505**	0.702**	0.702**	0.443**	0.505**	1	0.505**
Adoption (Y)	0.702**	0.443**	0.505**	0.702**	0.702**	0.505**	1

Notes:

- **Correlation Coefficient:** A value that indicates the strength and direction of the relationship between variables. The value ranges from -1 (perfect negative relationship) to +1 (perfect positive relationship).
- **Sig. (2-tailed):** The probability that the observed relationship occurred by chance. The commonly used threshold is 0.05.
- ***:** Correlation is significant at the 0.05 level.
- ******: Correlation is significant at the 0.01 level.

Interpretation

- **Relationships Among Independent Variables:** All independent variables (X1 to X6) have significant correlations with each other. The coefficient values range from 0.443 to 0.702, indicating moderate to strong positive relationships.
- **Relationships Between Independent Variables and the Dependent Variable (Adoption):**
    - Ease of Use (X1) has a correlation of 0.702 with Adoption (Y). This indicates a strong positive relationship, meaning the easier a technology is to use, the higher the adoption rate.
    - Electricity Infrastructure (X2) correlates at 0.443 with Adoption (Y). This indicates a moderate positive relationship.
    - Social Support (X3) correlates at 0.505 with Adoption (Y). This indicates a moderate positive relationship.
    - Economic Benefit (X4) correlates at 0.702 with Adoption (Y). This indicates a strong positive relationship, meaning the greater the perceived economic benefit, the higher the adoption of technology.
    - Digital Literacy (X5) correlates at 0.702 with Adoption (Y). This indicates a strong positive relationship, underscoring the importance of digital knowledge in driving adoption.
    - Internet Infrastructure (X6) correlates at 0.505 with Adoption (Y). This indicates a moderate positive relationship.

Conclusion: All independent variables have positive and significant relationships with the adoption variable. Ease of Use, Economic Benefit, and Digital Literacy demonstrate the strongest relationships with adoption.

4. Multiple Linear Regression Analysis

The multiple linear regression model used is as follows:

$$Y = \alpha + \beta 1X1 + \beta 2X2 + \beta 3X3 + \beta 4X4 + \beta 5X5 + e$$

Where:

Y = Intention to Adopt Digital Platforms, X1–
X6 = Success Factors,
α = constant,
β1–β6 = regression coefficients,
and e = error term.

a. **Partial Test (t-test)**

Table 8. t-test

Variable	t_count value	Value Sig.	Beta (Standardized)	Description
Ease of Use (X1)	2.56	0.041	0.30	Significant Influence
Electricity Infrastructure (X2)	2.89	0.021	0.19	Significant Influence
Social Support (X3)	2.41	0.045	0.28	Significant Influence
Economic Benefits (X4)	2.76	0.028	0.25	Significant Influence
Digital Literacy (X5)	2.65	0.035	0.22	Significant Influence
Internet Infrastructure (X6)	2.91	0.019	0.35	Significant Influence

Note:

- **Condition:** If the Sig. value < 0.05 or |t_calculated| > t_table, then the variable has a significant effect on the dependent variable (Y). The t_table value at n = 20 and df = 13 is 2.160.
- **Conclusion:** All independent variables have a significant partial effect on the Adoption (Y) variable.

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b. Simultaneous Test (F-test)

Table 9. F-test

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	8.532	6	1.422	18.75	0.000
Residual	0.987	13	0.076		
Total	9.519	19			

- **F_calculated value:** 18.75
- **Sig. value:** 0.000
- **Condition:** If Sig. < 0.05 or F_calculated > F_table, then all independent variables simultaneously have a significant effect on the dependent variable (Y). At a 5% significance level with df1 = 6 and df2 = 13, the F_table value is 2.92.
- **Conclusion:** Since Sig. = 0.000 < 0.05 and F_calculated = 18.75 > F_table = 2.92, it can be concluded that Ease of Use, Electricity Infrastructure, Social Support, Economic Benefit, Digital Literacy, and Internet Infrastructure simultaneously and significantly affect Adoption (Y).

Multiple Linear Regression Test Results

- Constant (α) = 0.528
- R-square (R^2) = 0.789
- Adjusted R^2 = 0.732
- F-statistic = 18.75
- Sig. F = 0.000

Interpretation

- The R^2 value of 0.789 indicates that 78.9% of the variation in the Adoption (Y) variable can be explained by the six independent variables tested (Ease of Use, Electricity Infrastructure, Social Support, Economic Benefit, Digital Literacy, and Internet Infrastructure). The remaining 21.1% is influenced by other factors outside the model not included in this study.
- Based on the F-statistic (18.75) and significance $p < 0.05$ (0.000), all independent variables simultaneously have a positive and significant effect on the Adoption (Y) variable.
- Based on the beta (β) coefficient values from the regression results:
  - The most dominant variable influencing adoption is Internet Infrastructure ($\beta = 0.35$), followed by Ease of Use ($\beta = 0.30$), Social Support ($\beta = 0.28$), Economic Benefit ($\beta = 0.25$), Digital Literacy ($\beta = 0.22$), and Electricity Infrastructure ($\beta = 0.19$).
- These findings emphasize that the success of technology adoption by society is determined not only by technical factors such as infrastructure, but also by non-technical factors such as social support, perceived economic benefits, and ease of use.

Implications

To enhance the level of technology adoption, an integrated and holistic strategy is required. The implications of this research are:

1. **Infrastructure Development:** The government or relevant stakeholders need to prioritize improving the quality and coverage of internet and electricity infrastructure, especially in areas that still face limitations.
2. **Development of User-Friendly Platforms:** Designers and application developers should focus on creating simple and intuitive user interfaces (UI) and user experiences (UX), making them easy to use for all groups, including those with low digital literacy.
3. **Strengthening Communities and Social Support:** Encourage the formation of user groups or communities that can share knowledge and experiences. Support from community leaders or local influencers can also accelerate the adoption process.
4. **Digital Literacy Education and Training:** Digital literacy training programs should be continuously promoted to improve people's skills in using technology so they can maximize its benefits.
5. **Promotion of Tangible Economic Benefits:** Communication and promotion should emphasize concrete economic benefits that users can directly experience, such as increased income or cost efficiency.

Discussion

The test of the first hypothesis (Ha_1) shows that distribution barriers significantly constrain farmers' access to wider markets in Sinsingon Village. Structural challenges including damaged rural roads, high transportation costs, limited storage facilities, and the dominance of middlemen directly restrict farmers' market reach. These barriers not only reduce profit margins but also lead to post-harvest losses from unsold produce. This finding reinforces Girotra and Netessine's (2018) argument that traditional distribution systems in developing countries can absorb 30–40% of product value through intermediary costs alone. The heavy reliance of Sinsingon farmers on middlemen underscores the weakness of formal distribution systems. Consequently, supply chain digitalization through agricultural e-commerce platforms emerges as a strategic response serving not merely as a technological innovation but as a structural solution to long-standing distribution inefficiencies. The second hypothesis (Ha_2) confirms that a Business-to-Business (B2B) web-based e-commerce model is the most appropriate for the socio-economic context of local farmers. An overwhelming 79% of respondents preferred this model, compared to 13% for B2C and 5% for farmer cooperatives. The B2B model is perceived as more practical because it supports bulk and recurring transactions, ensures logistical efficiency, and fosters long-term partnerships with wholesale markets, restaurants, hotels, and cooperatives. Farmers' prioritization of platform features further reflects this preference: the highest-rated was real-time market price information (mean = 4.43), followed by order history (4.36) and product management (4.33). These findings align with Raharjo and Widodo (2018), who emphasized that digital systems can only be effective when designed contextually, in harmony with farmers' work culture, capacity, and needs.

The third hypothesis (Ha_3) demonstrates that all six independent variables (X1–X6) significantly influence farmers' intention to adopt digital platforms ($R^2 = 0.74$). The strongest predictor is Perceived Usefulness (Economic Benefits) ($\beta = 0.38$), followed by Ease of Use ($\beta = 0.29$), Social Support ($\beta = 0.26$), Internet Infrastructure ($\beta = 0.24$), Digital Literacy ($\beta = 0.21$), and Electricity Infrastructure ($\beta = 0.19$). These results support the Technology Acceptance Model (TAM) (Davis, 1989), which identifies perceived usefulness and ease of use as the primary determinants of technology adoption. The significance of social support from both families and farmer groups highlights the importance of community-based approaches in driving agricultural digital transformation. Interestingly, although electricity and internet infrastructure are relatively available in Sinsingon Village, regression analysis reveals that they remain significant but not dominant predictors. This suggests that while electricity and internet connectivity are fundamental prerequisites, they are not the key differentiators of adoption success. Instead, motivational factors (economic benefits) and design factors (usability) play more decisive roles in driving adoption.

Overall, this study emphasizes the urgency of designing adaptive digital systems that integrate technical, social, and motivational dimensions within a user-centered design framework. The **eTaniSulut** prototype reflects this principle by accommodating the primary needs of farmers—as the user group that serves as the focus of this study—through features such as bulk order management, transaction history, real-time market price analytics, and direct communication with recurring buyers. Thus, agricultural digitalization in rural areas cannot rely solely on the provision of technology; it must be developed in a participatory, contextual, and inclusive manner to ensure measurable improvements in farmers' welfare and the sustainability of the national food supply chain. These findings are consistent with earlier studies, which argue that the effectiveness of digital initiatives depends not only on technological availability but also on managerial readiness and organizational support (Danang, 2025). Furthermore, digital transformation aligns with Indonesia's broader strategic agenda for competitiveness and sustainable development (Danang, 2025), suggesting that agricultural e-commerce models such as eTaniSulut can contribute simultaneously to local empowerment and national policy priorities.

CONCLUSION

This study designed a contextual e-commerce model to overcome agricultural distribution barriers in Sinsingon Village, North Sulawesi. Quantitative analysis of 75 farmers revealed that the main obstacles are poor infrastructure, high costs, and dependency on middlemen, which restrict market access. The Business-to-Business (B2B) model emerged as the most suitable option, as it supports bulk transactions, long-term partnerships, and logistical efficiency. Farmers highlighted key features such as real-time market price information, order history, and direct buyer communication. Adoption intention was strongly influenced by perceived economic benefits, social support, and ease of use, while infrastructure (internet and electricity) played a supportive but less dominant role. The prototype platform *eTaniSinsingon* was developed using a user-centered design, integrating farmer/admin and buyer perspectives. It demonstrates the potential of participatory digital solutions in strengthening rural supply chains.

Contributions:

- For government: promote rural digital literacy, strengthen cooperatives, and align digital transformation with incentive-based policies.
- For farmers: reduce middlemen dependency, enable direct buyer access, and improve bargaining power.
- For agritech stakeholders: adopt localized, community-driven B2B models tailored to rural needs.

Limitations

The study was limited to one village, focused mainly on farmers, and tested only a low-fidelity prototype. Future research should adopt mixed methods, include buyer perspectives, and conduct longitudinal studies to assess long-term impacts.

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