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Analysis of IoT Adoption Intention Among Horticulture Farmers: an Integration of the UTAUT Model and Trust in Technology

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Abstract

IoT-based tools can support more precise decisions in horticulture, but their use among Indonesian farmers is still limited. We investigated adoption intention and use behavior among 100 horticulture farmers in Bogor City using an extended UTAUT model that combines Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Perceived Trust in Technology. Survey responses were analyzed with PLS-SEM in SmartPLS 4. Effort Expectancy was the only significant predictor of Behavioral Intention ($\beta = 0.371$), and Behavioral Intention was significantly associated with Use Behavior ($\beta = 0.515$). Performance Expectancy, Social Influence, Facilitating Conditions, and Perceived Trust in Technology had no significant direct effects. The model accounted for 18.7% of the variance in Behavioral Intention and 26.2% in Use Behavior. For farmers at this early stage of IoT exposure, ease of use appears to matter more than expected performance gains or available support. Programs intended to broaden adoption should therefore emphasize simple interfaces, practical demonstrations, repeated training, and opportunities for farmers to learn by using the technology.

Keywords: Internet of Things (IoT); UTAUT; Perceived Trust in Technology; Behavioral Intention; Horticulture Farmers

1. Introduction

Horticultural production requires frequent decisions about water, soil conditions, crop development, and pest pressure, making timely field information especially valuable. IoT technologies can provide that information through connected sensors, automated irrigation, nutrient monitoring, yield estimation, and product-tracking systems [1]. When these tools work reliably, farmers can respond more quickly to changing field conditions and manage inputs with greater precision. The benefits observed in controlled environments, however, do not automatically transfer to everyday farming. Sensor accuracy can vary with soil conditions, electricity supply may be unstable, network coverage can interrupt data transmission, and devices must withstand prolonged exposure to field conditions. These practical issues shape whether farmers view IoT as a technology they can realistically depend on. For smallholders, these reliability questions are not secondary technical details; they determine whether a digital recommendation can be used safely in day-to-day crop management.

In this research, IoT adoption is bounded by six functions that are relevant to small- and medium-scale horticulture in Indonesia. The first is Soil and Environmental Condition Monitoring [2], [3], including soil moisture, temperature, pH, and microclimate sensing. The second is Water Resource Monitoring [4], [5], [6], which covers water-level, flow, and groundwater observation. Crop Growth Monitoring [7], [8] includes plant-health sensing, growth-stage detection, and canopy analysis. Irrigation Management [8], [9] covers automated drip irrigation, sprinkler control, and water-distribution adjustment, while Fertilizer Management [10], [11], [12] includes nutrient dosing, precision application, and nutrient mapping. The

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sixth category, Pest and Disease Management [9], [10], [13], covers early detection, sensor-assisted traps, and disease monitoring. These functions were selected because they are closer to the technical and financial reach of the target farmers than highly capital-intensive options such as autonomous harvesting or satellite-based precision systems. The scope therefore captures applications that farmers can encounter as stand-alone devices or as components of a simple smart-farming system, without assuming access to fully automated production.

Access to digital technology has not yet translated into broad IoT use among Indonesian farmers [2]. West Java statistics show that many farmers still do not use internet-based tools or smart-farming applications in routine agricultural work [14]. Bogor City presents a useful case because it is close to large urban markets and has comparatively favorable access to digital infrastructure, yet advanced agricultural technologies remain uncommon among horticulture farmers. This gap suggests that making a technology available is only one part of adoption. Farmers must also see the technology as understandable, relevant, trustworthy, and feasible within the conditions in which they actually farm. The contrast between general digital access and actual agricultural use is especially important because owning a smartphone or having an internet signal does not by itself indicate readiness to operate connected farm equipment. This distinction is central to the research problem. A farmer may be digitally connected for communication or market information while still having no experience with sensors, automated controls, or data-driven crop management. The adoption gap examined here concerns that more specialized level of technology use.

UTAUT provides a useful structure for examining these individual adoption decisions. The framework links Behavioral Intention and Use Behavior to four main factors: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions [15], [16]. Recent agricultural studies have applied UTAUT or related extensions to digital farming, precision agriculture, and IoT adoption across a range of national and farming contexts [2], [15]-[21]. Across this literature, expected usefulness, perceived effort, encouragement from relevant social groups, and access to supporting resources repeatedly appear as factors that can shape farmers' responses to new technologies. This structure is useful for the present study because it separates judgments about the technology itself from the intention to adopt it and from reported use behavior. Performance Expectancy captures anticipated gains from using the system, Effort Expectancy addresses the difficulty of learning and operating it, Social Influence reflects encouragement from relevant others, and Facilitating Conditions represent the resources that can support use. Behavioral Intention and Use Behavior then capture the movement from evaluation toward adoption.

An additional issue arises when farmers are asked to rely on technology that they have rarely used. In such settings, uncertainty may not be fully represented by the standard UTAUT constructs, which makes trust in the technology itself relevant. Recent work describes trust in technology in terms of beliefs that a system can function reliably and provide useful support, thereby reducing uncertainty about relying on it [22]. Evidence from digital agriculture likewise shows that confidence in technology performance can affect adoption decisions [23]. Related UTAUT, UTAUT2, and TAM-oriented studies have examined trust and other acceptance factors in agricultural and IoT settings [17], [18], [23]-[27]. For horticulture farmers, this issue is practical: an inaccurate sensor or unstable system can directly affect irrigation, fertilizer, or crop-protection decisions. Limited previous exposure, acquisition costs, and uncertainty about long-term performance may therefore influence how farmers judge IoT technologies in Bogor City. Trust is therefore treated as a perception formed around the technology's performance in use, rather than as a general attitude toward digitalization. For a farmer, trust can be tested in very practical ways: whether a moisture reading seems credible, whether an automated action occurs when expected, and whether the system remains usable when field conditions change. These judgments can shape reliance even before farmers develop a detailed view of the technology's economic return.

The contribution of this research is not limited to adding Perceived Trust in Technology to UTAUT. Previous studies mainly explain technology acceptance at the individual level, whereas official statistics describe broader patterns of digital adoption [14], [16], [18], [23]. These perspectives have rarely been examined together for horticulture farmers in Bogor. Using farmer-level data, this study examines which perceptions are associated with the low adoption pattern observed in the region. The results show that effort-related considerations are more immediate than performance expectations, social influence, facilitating conditions, or perceived trust at this stage of adoption. This provides a behavioral explanation for why digital infrastructure and the expected benefits of IoT do not necessarily result in widespread use. The analysis also avoids assuming that factors found significant in more mature technology settings will have the same weight where exposure remains low. Regional statistics can show that IoT adoption is low, but they cannot explain why individual farmers hesitate to use the technology. Farmer-level analysis can address this limitation by identifying the perceptions associated with adoption intention and use.

Accordingly, the study evaluates how the UTAUT constructs and Perceived Trust in Technology relate to IoT adoption intention and use behavior among horticulture farmers in Bogor City. The local focus allows the analysis to capture an adoption environment in which direct experience with IoT remains limited. Beyond testing the proposed relationships, the study is intended to identify which barriers deserve priority in extension programs, technology design, and public support for digital agriculture, particularly with respect to usability, farmer capability, and confidence in the technology. The study therefore examines both the significant relationships and what they mean for the next stage of farmer adoption.

2. Research Methodology

a. Research Design

A quantitative confirmatory design was used because the research tests relationships specified before data analysis rather than searching for new constructs [28]. The empirical model combines UTAUT with Perceived Trust in Technology and applies it to IoT adoption by horticulture farmers. Data were collected once through a structured cross-sectional questionnaire, allowing the same set of perceptions, intentions, and self-reported use measures to be obtained from every respondent. Using a single survey instrument also ensured that the constructs were measured under the same field conditions and within the same adoption period. The design was confirmatory because the constructs, indicators, and directional hypotheses were specified before the main sample was analyzed.

The resulting conceptual model places the four UTAUT predictors and Perceived Trust in Technology in the same structural framework for explaining farmer adoption. Figure 1 shows the proposed paths evaluated in the PLS-SEM analysis.

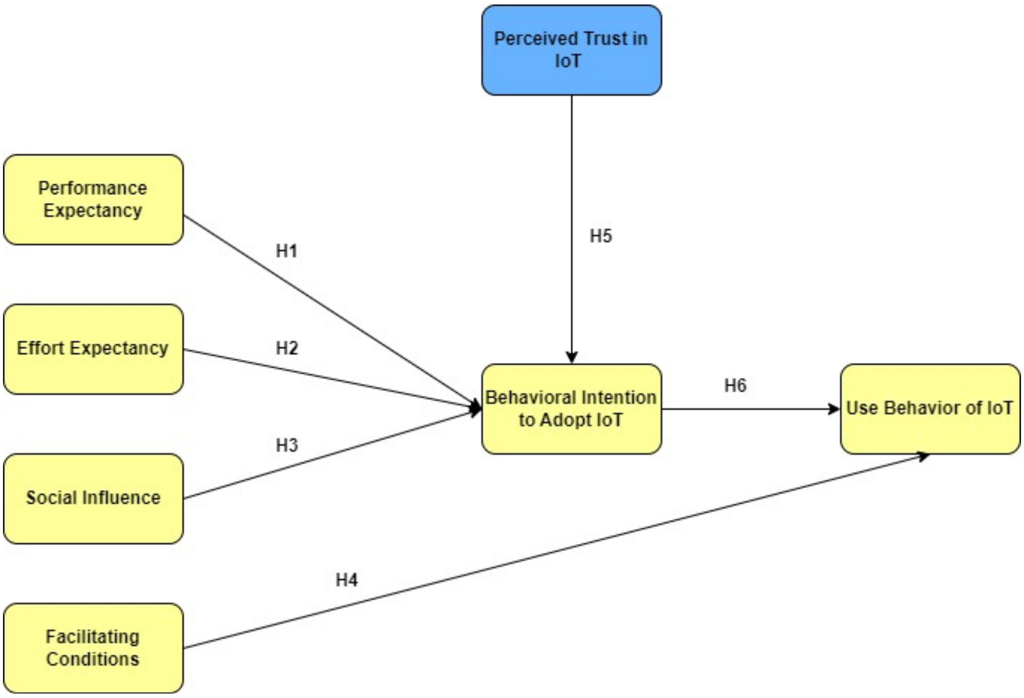

Figure 1. Research Model of IoT Adoption among Horticulture Farmers

b. Scope of IoT Technologies Examined

Table 1 specifies the six IoT functions used to define the technology scope and gives representative devices and farming uses for each category.

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Table 1. Scope of IoT Technologies Examined

Category	Representative Technologies	Primary Applications
Soil and Environmental Condition Monitoring [2], [3]	Soil moisture sensors, temperature probes, pH sensors, EC sensors, ambient weather stations	Real-time monitoring of soil water content, nutrient levels, and microclimate conditions to optimize irrigation timing and fertilizer application
Water Resource Monitoring [4], [5], [6]	Water level sensors, flow meters, pressure sensors, groundwater monitoring systems	Tracking water availability, consumption rates, and distribution efficiency to prevent water scarcity and optimize resource allocation
Crop Growth Monitoring [7], [8]	Plant health sensors, NDVI cameras, growth stage detectors, canopy temperature sensors	Early detection of growth anomalies, stress indicators, and developmental stages to enable timely interventions
Irrigation Management [8], [9]	Automated drip systems, smart sprinklers, valve controllers, soil-moisture-based automation	Precision water delivery based on real-time soil moisture data, reducing water waste and improving crop water use efficiency
Fertilizer Management [10], [11], [12]	Nutrient dosing systems, precision applicators, soil nutrient mapping sensors, fertigation controllers	Optimized nutrient application based on soil analysis and crop requirements, minimizing over-fertilization and environmental impact
Pest and Disease Management [9], [10], [13]	Insect traps with sensors, disease detection cameras, environmental condition monitors for pest prediction	Early warning systems for pest outbreaks and disease occurrence, enabling preventive rather than reactive pest control measures

c. Research Location and Unit of Analysis

Bogor City, West Java, was selected as the study area because horticulture is an established activity there and farmers operate close to major urban markets. The city also provides a useful contrast: digital infrastructure is relatively accessible, but advanced farm technologies such as IoT are still not widely used. This combination makes Bogor City appropriate for observing adoption at an early diffusion stage [29]. This setting allows the study to distinguish between the availability of general infrastructure and farmers' willingness to adopt a specialized digital farming technology.

The unit of analysis is the individual horticulture farmer. Performance Expectancy, Effort Expectancy, Perceived Trust in Technology, Behavioral Intention, and Use Behavior all represent judgments or actions made at the farmer level. Each respondent was therefore treated as the decision-maker who assesses whether an IoT application is useful, manageable, reliable, and feasible for his or her own farming activities.

d. Population and Sample

The study population consists of horticulture farmers in Bogor City. Official city statistics report approximately 1,437 farmers across vegetable, fruit, ornamental-plant, and medicinal-plant subsectors [29]. The population includes farmers with different levels of digital exposure, from those who have used digital tools to those with no prior IoT adoption.

Respondents were selected through proportional random sampling across the six districts of Bogor City so that the sample followed the geographical distribution of the farmer population. Minimum sample size was checked before data collection with an a priori G*Power analysis for linear multiple regression (fixed model, R^2 deviation from zero). With $f^2 = 0.15$, $\alpha = 0.05$, power = 0.85, and four predictors for the main endogenous construct, the analysis required at least 95 observations. The final sample of 100 farmers therefore exceeded the minimum requirement for the planned hypothesis tests [30], [31]. The power

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calculation was used as a minimum adequacy check rather than as a substitute for the sampling design, which remained proportional to the farmer distribution across districts. The proportional allocation was intended to prevent districts with larger farmer populations from being underrepresented. At the same time, the power analysis provided an independent statistical check that the number of observations was sufficient for the main endogenous equation.

e. Instrument Development and Measurement

Data were obtained with a structured questionnaire divided into two parts. The first recorded respondent characteristics: age, education, farming experience, land size, digital-device access, internet availability, and previous IoT-related training. These variables were used to describe who participated in the survey and the digital conditions surrounding their farming activities.

The second part contained the indicators for the research constructs. Items from previously validated measures were adapted to an agricultural IoT setting. The UTAUT block covered Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC); Perceived Trust in Technology (PT) was added to represent confidence in IoT safety, reliability, and usefulness. Behavioral Intention (BI) and Use Behavior (UB) were modeled as endogenous constructs. Responses to all indicators used a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree).

Before the main survey, the instrument was reviewed by experts and piloted with 30 horticulture farmers. The pilot was used to check whether the wording was understandable and appropriate for the local farming context. Minor wording changes were made where respondents could misinterpret an item, after which the revised questionnaire was used for the 100-person survey.

f. Data Analysis Technique

PLS-SEM was performed using SmartPLS 4 to estimate the structural relationships and explained variance among the latent constructs. This method is suitable for prediction-oriented analysis and does not require multivariate normality in the same way as covariance-based SEM.

Model assessment was carried out in two steps. First, the measurement model was checked for reliability and validity. Outer loadings of at least 0.70 and AVE values of at least 0.50 were used for convergent validity, while Cronbach's Alpha and Composite Reliability values above 0.70 were used for internal consistency. Discriminant validity was evaluated with HTMT, using 0.90 as the upper criterion [30], [31].

One Use Behavior indicator did not meet the required outer-loading level and was removed during measurement-model assessment. Removing that item improved the reliability and convergent validity of Use Behavior while leaving the construct definition and structural paths unchanged.

Second, the structural model was examined through path coefficients, R^2, and f^2. Statistical significance was estimated by bootstrapping 5,000 subsamples, from which t-statistics and p-values were obtained for the six hypothesized paths. The resulting estimates were then used to determine which relationships were supported by the farmer data.

g. Research Hypotheses

Six directional hypotheses were specified from the proposed UTAUT-plus-trust model. They test how farmers' evaluations of the technology relate to Behavioral Intention and how Behavioral Intention and Facilitating Conditions relate to Use Behavior:

- **H1:** Performance Expectancy (PE) has a positive effect on Behavioral Intention (BI).
- **H2:** Effort Expectancy (EE) has a positive effect on Behavioral Intention (BI).
- **H3:** Social Influence (SI) has a positive effect on Behavioral Intention (BI).
- **H4:** Facilitating Conditions (FC) have a positive effect on Use Behavior (UB).
- **H5:** Perceived Trust in Technology (PT) has a positive effect on Behavioral Intention (BI).
- **H6:** Behavioral Intention (BI) has a positive effect on Use Behavior (UB).

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3. Results and Discussion

a. Results

1. Descriptive Overview of Respondents

The survey produced 100 usable responses from horticulture farmers in Bogor City. Participants came from vegetable, fruit, ornamental-plant, and medicinal-plant farming, with considerable variation in age, schooling, farming experience, landholding, device access, and internet conditions. This variation is useful for the analysis because the sample includes farmers facing different levels of digital readiness rather than a single technologically homogeneous group. It also reflects the practical diversity expected in a citywide farmer population rather than a sample restricted to technology users. The respondent profile also includes both farmers who are already comfortable with smartphones and farmers whose digital use remains limited. This range is relevant because IoT adoption may depend on the distance between familiar digital practices and the more specialized demands of connected agricultural tools.

Table 2. Demographic Profile of Respondents

Variable	Category	Frequency	Percentage (%)
Gender	Male	76	76
	Female	24	24
Age group	<25 years	7	7
	25–29 years	25	25
	30–34 years	34	34
	≥35 years	34	34
Education level	No schooling	7	7
	Primary	22	22
	Junior high	17	17
	Senior high	33	33
	Diploma (D1–D3)	8	8
	Bachelor (D4/S1)	12	12
	Postgraduate (S2/S3)	1	1
Farming experience	<5 years	15	15
	5–10 years	18	18
	11–15 years	23	23
	16–20 years	20	20
	>20 years	24	24
Main commodity	Vegetables	52	52
	Fruits	23	23
	Ornamental plants	13	13
	Medicinal plants	12	12
Land size	<0.5 ha	47	47
	0.5–1 ha	27	27
	1–2 ha	20	20
	>2 ha	6	6
Smartphone ownership	No	4	4
	Yes	96	96
Smartphone use for farming	Rarely/Not used	11	11
	Sometimes	48	48
	Active use	41	41
IoT experience	Never	67	67
	Heard only	24	24

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Variable	Category	Frequency	Percentage (%)
Internet access	Used	9	9
	Not available	16	16
	Unstable	60	60
	Stable	24	24
IoT-related training	Never	74	74
	Ever	26	26

Table 2 shows that 76% of respondents are men. The two largest age groups are 30-34 years and 35 years or older, each accounting for 34% of the sample. Formal education is concentrated at the secondary level or below: 33% completed senior high school, while 39% reported primary or junior-high education. The profile indicates that many respondents have limited formal preparation for working with advanced digital systems.

Farm size is also modest. Nearly half of the respondents (47%) cultivate less than 0.5 ha, and another 27% manage 0.5-1 ha. Although 96% own a smartphone, ownership does not mean that the device is routinely used for farming: only 41% reported active agricultural use, while the rest use smartphones occasionally or not at all for farm activities.

Direct exposure to IoT is much lower than basic smartphone access. Sixty-seven percent of respondents have never used IoT, only 9% report hands-on experience, and 74% have never attended IoT-related training. Connectivity is another constraint, as 60% describe their internet connection as unstable and only 24% report stable access. Taken as a profile of the study setting, these figures show that farmers have basic digital access but limited practical readiness for more advanced connected technologies. The gap between device ownership and IoT experience is important when interpreting the structural model because several constructs ask respondents to evaluate a technology that many have not yet used directly.

2. Measurement Model Evaluation

Before testing the hypotheses, the reflective measurement model was checked to determine whether the indicators measured their intended constructs consistently. The assessment covered internal consistency, convergent validity, and discriminant validity using the criteria specified in the methodology.

Table 3 reports Cronbach's Alpha and Composite Reliability for each construct. Every value is above 0.70, so none of the constructs shows an internal-consistency problem. The result indicates that the retained items within each scale move together sufficiently to represent the same latent variable.

AVE values in Table 3 are also above 0.50 for all constructs. This means that each latent variable accounts for more than half of the variance in its retained indicators. Together with the acceptable outer loadings, the AVE results support convergent validity.

Table 3. Measurement Model Assessment (Reliability and Convergent Validity)

Construct	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
BI	0.740	0.851	0.656
EE	0.813	0.889	0.727
FC	0.823	0.890	0.730
PE	0.739	0.829	0.621
PT	0.824	0.887	0.724
SI	0.865	0.915	0.781
UB	0.786	0.903	0.823

On the basis of these values, all seven constructs met the reliability and convergent-validity criteria used in this study.

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HTMT was then used to check whether any pair of constructs overlapped excessively. All coefficients in Table 4 are below 0.90; the highest is 0.666 between BI and UB. The constructs can therefore be treated as empirically distinguishable in the subsequent structural analysis.

Table 4. Discriminant Validity (HTMT Criterion)

	BI	EE	FC	PE	PT	SI	UB
BI	—						
EE	0.480	—					
FC	0.273	0.239	—				
PE	0.191	0.073	0.122	—			
PT	0.192	0.151	0.180	0.105	—		
SI	0.174	0.087	0.147	0.142	0.183	—	
UB	0.666	0.114	0.111	0.144	0.079	0.106	—

The measurement checks did not identify a reliability or validity problem that would prevent structural-model testing. The retained indicators and constructs were therefore carried forward to the path analysis.

3. Structural Model Evaluation

Structural-model assessment focused on the six hypothesized relationships after the measurement criteria had been satisfied. R² was used to describe explained variance, f² to gauge the contribution of individual predictors, and bootstrap estimates from 5,000 resamples to evaluate statistical significance.

Figure 2 displays the estimated model, including standardized path coefficients and the R² values for the two endogenous constructs.

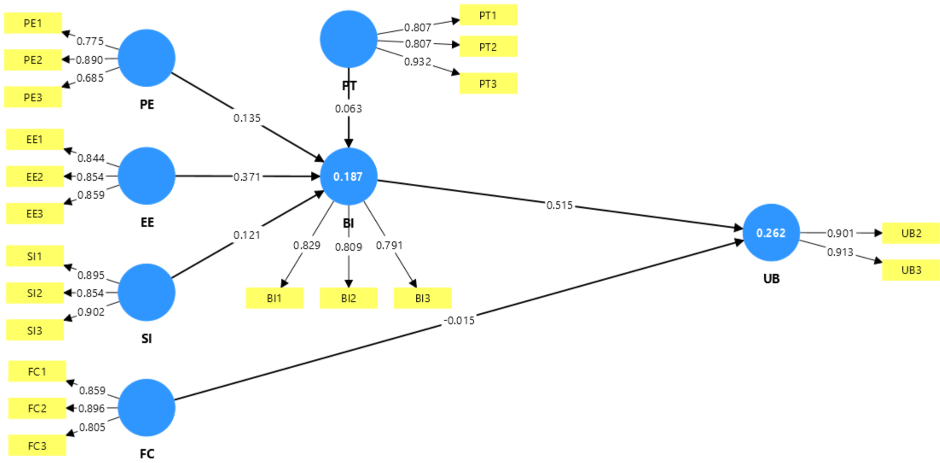

Figure 2. Results of the Structural Model (PLS-SEM)

The pattern in Figure 2 is uneven across predictors of Behavioral Intention. Effort Expectancy has the largest positive coefficient, whereas Performance Expectancy, Social Influence, and Perceived Trust in Technology contribute only weakly. For these farmers, the model therefore points more strongly to perceived ease of use than to expected benefits, social pressure, or trust as an immediate basis for intention. The contrast is visible in the size of the coefficients before statistical significance is considered and becomes clearer in the bootstrap tests reported below.

Behavioral Intention shows a much stronger positive association with Use Behavior. In practical terms, respondents who report a stronger intention to adopt IoT also report greater use behavior. This relationship places intention at the center of the observed transition from favorable perceptions to reported use. The result does not mean that every farmer with intention is already a regular IoT user. Use Behavior is self-reported and the sample contains many non-users, so the coefficient is interpreted as an association between stronger intention and higher reported engagement rather than proof of sustained routine use.

The structural pattern is consistent with an early adoption setting, usability and willingness to try the technology explain more of the observed behavior than the other modeled conditions. The following sections quantify that pattern through R^2, path significance, and effect-size results.

4. Coefficient of Determination (R^2)

Behavioral Intention has an R^2 of 0.187. Thus, Performance Expectancy, Effort Expectancy, Social Influence, and Perceived Trust in Technology jointly account for 18.7% of its variance. For Use Behavior, R^2 is 0.262, meaning that Behavioral Intention and Facilitating Conditions explain 26.2% of the observed variance (Table 5).

Table 5. Coefficient of Determination (R^2)

Endogenous Construct	R^2 Value	Interpretation
Behavioral Intention (BI)	0.187	Low to moderate explanatory power
Use Behavior (UB)	0.262	Moderate explanatory power

The two R^2 values show that much of the variation in adoption remains outside the present model, especially for Behavioral Intention. That result is plausible in a setting where most respondents have little or no direct IoT experience, because cost, compatibility, risk, local support, and other unmeasured conditions may also influence adoption. The R^2 values should therefore be read as a description of the model's current coverage, not as evidence that adoption decisions can be reduced to the included constructs.

5. Path Coefficients and Hypothesis Testing

Bootstrapping with 5,000 resamples was used to test all six paths. Table 6 presents the coefficients together with their t-values, p-values, f^2 values, and hypothesis decisions.

Table 6. Structural Model Results and Hypothesis Testing

Hypothesis	Path	β (Path Coefficient)	t-value	p-value	f^2	R^2	Result
H1	PE → BI	0.135	1.056	0.291	0.022	0.187	Not supported
H2	EE → BI	0.371	4.380	0.000	0.167	0.187	Supported
H3	SI → BI	0.121	1.190	0.234	0.018	0.187	Not supported
H4	FC → UB	−0.015	0.133	0.894	0.000	0.262	Not supported
H5	PT → BI	0.063	0.485	0.628	0.005	0.187	Not supported
H6	BI → UB	0.515	6.796	0.000	0.342	0.262	Supported

Only Effort Expectancy has a statistically significant direct relationship with Behavioral Intention ($\beta = 0.371$, $t = 4.380$, $p < 0.001$). Its f^2 of 0.167 indicates a medium contribution to the explanation of intention. Performance Expectancy, Social Influence, and Perceived Trust in Technology have positive coefficients, but none reaches statistical significance in this sample.

For Use Behavior, Behavioral Intention is significant and comparatively strong ($\beta = 0.515$, $t = 6.796$, $p < 0.001$; $f^2 = 0.342$). Facilitating Conditions, by contrast, are essentially unrelated to reported use ($\beta = -0.015$, $p = 0.894$). The data therefore indicate that available support or infrastructure does not translate directly into use unless farmers have first developed an intention to adopt the technology.

6. Effects on Behavioral Intention (BI)

Effort Expectancy is the strongest predictor of Behavioral Intention and the only one supported statistically ($\beta = 0.371$, $t = 4.380$, $p < 0.001$; $f^2 = 0.167$). H2 is therefore supported. The result means that, within this sample, farmers who perceive IoT as easier to learn and operate are more likely to express an intention to adopt it.

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Performance Expectancy has a small positive coefficient but is not significant ($\beta = 0.135$, $t = 1.056$, $p = 0.291$; $f^2 = 0.022$). Expected gains in productivity or work performance therefore do not distinguish farmers with stronger adoption intentions in the present sample, so H1 is not supported.

Social Influence also fails to reach significance ($\beta = 0.121$, $t = 1.190$, $p = 0.234$; $f^2 = 0.018$). Encouragement from peers or extension-related actors appears to have only a small association with intention at this stage, and H3 is not supported.

Perceived Trust in Technology has the smallest coefficient among the predictors of Behavioral Intention ($\beta = 0.063$, $t = 0.485$, $p = 0.628$; $f^2 = 0.005$). Confidence in IoT reliability and usefulness is therefore not a significant direct predictor in these data, leading to rejection of H5.

7. Effects on Use Behavior (UB)

Behavioral Intention is positively related to Use Behavior ($\beta = 0.515$, $t = 6.796$, $p < 0.001$; $f^2 = 0.342$), providing support for H6. The size of the coefficient indicates that reported use is markedly higher among farmers who already express a clear intention to adopt IoT.

Facilitating Conditions do not have a significant direct effect on Use Behavior ($\beta = -0.015$, $t = 0.133$, $p = 0.894$; $f^2 = 0.000$). Infrastructure, technical assistance, and other enabling resources therefore show no independent contribution to reported use in this model, and H4 is not supported.

8. Key Findings

Two relationships define the main empirical result. Ease of use, represented by Effort Expectancy, is associated with stronger Behavioral Intention, and Behavioral Intention is then strongly associated with Use Behavior. The remaining UTAUT and trust variables have limited direct effects. For farmers with little prior IoT exposure, adoption therefore appears to begin with whether the technology feels manageable and whether that perception develops into a concrete intention to use it.

b. Discussion

The results portray IoT adoption in Bogor horticulture as a process that is still close to its starting point. Within the extended UTAUT model, the significant paths are concentrated around Effort Expectancy and Behavioral Intention, while several factors that are important in more mature adoption settings are not yet statistically prominent.

1. The Central Role of Effort Expectancy and Behavioral Intention

Effort Expectancy is the only significant antecedent of Behavioral Intention and has a medium effect size. This result is consistent with the respondent profile: most farmers operate on small plots, few have used IoT directly, and formal IoT training is uncommon. Under those conditions, a system that appears difficult to learn or operate creates an immediate barrier, whereas a system perceived as straightforward is more likely to receive serious consideration. The significant path is therefore consistent with a situation in which the first adoption question is practical - 'Can I use this?' - before farmers move to more complex evaluations of return, trust, or support.

Comparable studies also report that ease of use and lower technological complexity can strengthen farmers' acceptance of digital agriculture [15], [20], [23]. For the Bogor respondents, this issue is likely to be concrete rather than abstract. Farmers must be able to understand what a sensor or application is telling them and fit the tool into existing routines; otherwise, expected benefits alone may not be enough to justify adoption. This interpretation also fits the large difference between smartphone ownership and direct IoT experience in the sample, showing that familiarity with everyday digital devices does not automatically remove the learning barrier for agricultural IoT.

Behavioral Intention is also strongly associated with Use Behavior. The finding is compatible with the UTAUT view that intention is close to the act of using a technology, but here the interpretation should remain tied to self-reported behavior. Even where support systems are imperfect, farmers who have already formed a clear intention are much more likely to report engaging with IoT.

2. Understanding the Non-Significant Effects: A Stage-of-Adoption Perspective

The non-significant paths provide useful information about the adoption stage rather than simply representing failed hypotheses. Performance Expectancy, Social Influence, Facilitating Conditions, and Perceived Trust in Technology may matter under other conditions, but the present data show that they are not direct drivers for this group of farmers. The interpretation is therefore conditional on the sampled setting. The study does not conclude that the four constructs are irrelevant to agricultural IoT in general; it shows that their direct effects are weak under the present combination of low exposure, limited training, and early diffusion.

Performance Expectancy may be difficult for respondents to judge because most have not yet seen IoT produce measurable gains on their own farms. With 67% reporting no IoT experience and 74% reporting no IoT-related training, claims about higher productivity or efficiency can remain theoretical. Until farmers observe results in comparable farming situations, expected performance benefits may carry less weight than the immediate question of whether the technology is easy to use. This does not mean that farmers disregard productivity; rather, the benefit may be difficult to quantify before they have observed a device working through a crop cycle or a repeated management task.

Social Influence shows a similar early-stage pattern. Regional data indicate that advanced digital farming is still uncommon in West Java [14], leaving relatively few experienced users who can serve as credible examples for other farmers. Where peer experience is scarce, recommendations from neighbors, farmer groups, or institutions may not yet exert the social pressure typically observed after a technology becomes more visible. As adoption becomes more visible, this mechanism could change because successful users would provide local evidence that is currently limited.

The result for Facilitating Conditions suggests that support resources alone are not enough to produce use behavior. Internet access, technical assistance, devices, or other enabling conditions can make adoption possible, but they do not create a reason to use IoT when farmers have not yet developed the intention or confidence to do so.

Perceived Trust in Technology is also non-significant. One explanation is that trust requires experience on which to base a judgment, while most respondents have had little direct interaction with IoT. Evidence from digital agriculture suggests that trust can develop as users observe technology performance over time [23]. In Bogor, trust may therefore become more consequential after farmers have accumulated successful or unsuccessful experience with the systems.

3. Behavioral Intention as a Linking Mechanism

The significant EE -> BI and BI -> UB paths form a clear sequence in the structural results. Farmers who view IoT as easier to handle tend to report stronger adoption intentions, and those with stronger intentions report higher Use Behavior. This sequence shows where Behavioral Intention sits in the observed adoption process without claiming an indirect effect that was not formally estimated.

For that reason, Behavioral Intention is treated here as a linking mechanism rather than a statistically established mediator. The study did not test a specific indirect effect from Effort Expectancy to Use Behavior through Behavioral Intention. The interpretation is therefore limited to the two supported direct relationships and to their logical connection within the proposed model.

4. Theoretical Contributions

The results suggest that UTAUT constructs may not carry the same weight when farmers have very limited experience with the technology. In this sample, Effort Expectancy is already relevant, whereas performance, social, support, and trust-related factors are not yet significant. The weak effect of Perceived Trust in Technology is worth noting because most respondents have had little opportunity to evaluate IoT performance directly. Longitudinal research could examine whether trust becomes more important after farmers gain experience through training, trials, or repeated use.

5. Contextual Implications in Relation to Statistics Indonesia (BPS), West Java Province Data

The farmer-level results are consistent with the broader picture reported by Statistics Indonesia (BPS), West Java Province, where advanced digital practices remain limited [14]. The two sources of evidence operate at different levels, but they point in the same direction, IoT use is still at an early stage. In that setting, the prominence of usability and individual intention in the survey provides a behavioral explanation for why wider digital availability has not yet produced routine IoT use. This correspondence does not establish generalizability beyond the sample, but it gives the micro-level findings a clear regional context.

4. Conclusion

The results show a relatively simple pattern of IoT adoption among horticulture farmers in Bogor City. Effort Expectancy significantly affects Behavioral Intention, and Behavioral Intention, in turn, has a significant effect on Use Behavior. Performance Expectancy, Social Influence, Facilitating Conditions, and Perceived Trust in Technology do not show significant direct effects in the model. Behavioral Intention accounts for 18.7% of the explained variance, while the model explains 26.2% of Use Behavior. In this setting, farmers appear to respond more strongly to technologies that are easy to understand and operate than to expected performance gains, social encouragement, available support, or trust-related considerations.

The results also suggest several practical priorities. For policymakers, introducing more sophisticated technology is unlikely to be sufficient if farmers find it difficult to use. Programs may be more effective when they focus on affordable, task-specific applications that address familiar farming activities, such as irrigation monitoring or crop-condition alerts. Agricultural extension services can support this process through field demonstrations, repeated practice, and direct assistance rather than one-off training sessions. For technology developers, the same finding highlights the value of simple interfaces, limited configuration requirements, and compatibility with smartphones already used by farmers. The immediate challenge is therefore not only providing IoT technology, but making it workable in farmers' daily routines.

The findings also need to be read within the limits of the study. Data were collected at one point in time, so changes in farmers' intentions, trust, and technology use could not be observed as their experience developed. Use Behavior was measured through self-reported responses, although many respondents had little direct experience with IoT systems, which may have affected how they answered these items. In addition, the respondents were drawn only from Bogor City. The results therefore describe this particular setting and may not fully represent farmers working under different infrastructure, institutional, or market conditions.

Further work could follow farmers over time to see whether the relative importance of these factors changes after they gain direct experience with IoT. Research across several regions would also help determine whether the relationships found in Bogor are specific to the local context or appear more broadly. Other factors, including perceived cost, government support, risk perception, and compatibility with existing farming practices, could be incorporated into the model. Farmer characteristics such as age, education, farming experience, and prior exposure to digital technology may also be examined as moderators. This would allow future studies to investigate more precisely when trust, social influence, and facilitating conditions begin to matter as adoption moves from initial interest toward regular use.

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