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Analysis of Farmers' Acceptance Factors for Digital Pond Management Applications Using the UTAUT2 Model

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Abstract

The shrimp farming industry is crucial to Indonesia's economy but faces challenges such as declining exports, low productivity, and limited technology adoption. Digital tools have been developed to support pond management through real-time water quality monitoring and data-based decision-making; however, user engagement remains low, indicating a gap between technology provision and adoption. This study aims to analyze factors influencing farmers' acceptance of such digital technologies using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model. A quantitative survey involving 140 shrimp farmers in Central Java was analyzed using Partial Least Squares–Structural Equation Modeling (PLS-SEM). The results show that performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit significantly affect behavioral intention, while behavioral intention weakly influences actual use behavior, revealing an intention behavior gap. In contrast, use behavior is strongly driven by habit and facilitating conditions, and price value negatively affects intention. The study concludes that habitual use and technical support are more decisive than intention in promoting technology adoption, providing theoretical insights and practical implications for developers to focus on habit-forming design and continuous support for digital transformation in aquaculture.

Keywords

Aquaculture, Digital Adoption, PLS-SEM, Technology Acceptance, UTAUT2.

1. Introduction

The shrimp farming industry, as one of Indonesia's key export sectors, has recently faced critical challenges that threaten its sustainability and competitiveness. Exports of frozen *vannamei* products decreased by 4% in 2022 and 9% in 2023, while deteriorating water quality, rising operational costs, and low production efficiency have simultaneously constrained small and medium scale farmers (Mustafa et al., 2023). In shrimp farming systems, the accumulation of organic waste from feed residues and feces triggers fluctuations in water quality. The instability of important parameters such as dissolved oxygen and brightness is a major factor that suppresses productivity and increases the risk of crop failure, especially for small- and medium-scale farmers who have limitations in management and technology (Rahmi et al., 2023).

In addition, high operational costs, especially feed and energy costs, are a huge burden for smallholder farmers, limiting their capacity to scale their businesses. The low technical efficiency in the use of production inputs also exacerbates the condition, as most farmers have not been able to optimize their existing resources to achieve maximum yields (Ariyadi, 2021; Mira et al., 2022; Purnamasari et al., 2023; Garlock et al., 2024). Advances in digital technology have driven the adoption of various data-driven solutions in shrimp farming, such as the use of IoT-based monitoring systems and pond management applications. In Indonesia, one of the innovations that is quite prominent is the JALA App, which presents real-time water quality monitoring and cultivation management features to improve operational efficiency (Yi et al., 2018; Mahmud et al., 2023; Quinde et al., 2024; Thangam et al., 2024).

Although it offers significant benefits, the level of use of the JALA App is still limited. Of the approximately 20.000 registered users, only 2.100 are recorded as active every month. This figure clearly shows the gap between the provision of technology and its acceptance at the user level. This gap is in line with various studies that have identified barriers to the adoption of digital technologies, such as the perception of the complexity of innovation, limited resources or funds, as well as low social trust among farmers (Purnamasari et al., 2023; Mahmud et al., 2023; Farkan et al., 2024). In the context of aquaculture, these challenges are unique because production success is highly sensitive to rapid environmental changes, making real-time decision-making essential. Unlike agriculture or livestock, shrimp ponds require continuous monitoring due to the biological fragility of shrimp, which increases the importance of technology adoption. To understand the root cause of this gap systematically, a comprehensive theoretical framework is needed. Thus, the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) paradigm is used in this study. UTAUT2 is a technology acceptance model developed by Venkatesh et al. (2012) to explain the factors that influence technology use intentions and behaviors, by adding hedonistic motivation constructs, price values, and habits to previous UTAUT models, which have proven effective in analyzing the various psychological and environmental factors that influence technology acceptance (Aloyshima et al., 2020; Sharma et al., 2024).

This model consists of seven independent constructs, namely performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit which are assumed to affect two dependent constructs, namely behavioral intention and use behavior. However, despite its relevance, existing studies have rarely focused on small- and medium-scale shrimp farmers in developing countries, creating a research gap regarding how resource constraints, experience, and farming characteristics shape technology acceptance in aquaculture.

This study aims to analyze the factors influencing farmers' acceptance of the JALA App using the UTAUT2 framework, focusing on small- and medium-scale farmers who face constraints in capital, technology access, and management capacity. These limitations contribute to low adoption rates compared to large-scale farmers, as also indicated by JALA's internal data and prior literature on digital innovation gaps in smallholder contexts. The study explicitly formulates three research questions concerning the extent to which UTAUT2 variables influence behavioral intention, the extent to which intention and habit determine actual usage, and the extent to which the UTAUT2 model explains adoption patterns among small- and medium-scale shrimp farmers. Through these inquiries, the study aims to strengthen the theoretical understanding of digital technology adoption and provide practical insights for supporting digital transformation in aquaculture.

2. Literature Review and Hypothesis Development

2.1. The Determinants of Behavior Intention

Performance expectancy refers to the extent to which farmers believe technology will enhance agricultural productivity and efficiency. Studies show a strong link between performance expectancy and adoption intention. Daum et al. (2023) found that perceived performance benefits drive farmers' intention to use precision farming tools. Similarly, Caffaro et al. (2020) and Eastwood et al. (2019) emphasize that expected improvements in productivity, decision-making quality, and operational efficiency are key motivators for adopting agricultural technology. Effort expectancy reflects perceived ease of use. In agricultural contexts with varied digital literacy, user-friendliness is critical. Benyam et al. (2021) highlight that complexity hinders adoption, especially among older farmers, while Kernecker et al. (2020) show that intuitive interfaces and simplified procedures increase adoption intention.

Social influence involves peer opinions, extension service recommendations, and community norms. Dessart et al. (2019) emphasize that social influence and community learning significantly affect the adoption of sustainable practices, and Klerkx and Begemann (2020) note that recommendations from trusted sources enhance adoption likelihood. Facilitating conditions refer to the availability of resources and infrastructure, such as internet access, technical support, and training. Fielke et al. (2020) note that inadequate infrastructure is a major barrier, while Takahashi et al. (2020) and Baumüller (2018) demonstrate that access to devices, internet, and comprehensive training increases adoption rates.

Hedonic motivation relates to enjoyment and satisfaction from using technology. Michels et al. (2020), Scholz et al. (2018), and Carrer et al. (2022) find that positive user experiences, gamification, and engaging feedback enhance motivation and adoption of agricultural technologies. Price value reflects the trade-off between perceived benefits and costs. Lowenberg-DeBoer et al. (2020), Blasch et al. (2022), and Caffaro et al. (2020) show that perceived economic value and transparent cost-benefit analyses strongly influence farmers' willingness to adopt precision agriculture. Habit refers to automatic use through repeated behavior. Barnes et al. (2019), Michels et al. (2020), and Moghavvemi et al. (2021) emphasize that established digital habits increase adoption intention and sustained use of agricultural technologies.

H1: Performance expectancy has a significant effect on farmers' behavioral intention.
H2: Effort expectancy has a significant effect on the behavioral intention.
H3: Social influence has a significant effect on the behavioral intention.
H4: Facilitating conditions has a significant effect on the behavioral intention.
H5: Hedonic motivation has a significant effect on the behavioral intention.
H6: Price value has a significant effect on the behavioral intention.

H7: Habit has a positive effect on the behavioral intention.

2.3. The Determinants of Use Behavior

Facilitating conditions refer to the extent individuals believe organizational and technical infrastructure supports system use. Venkatesh et al. (2012) note that adequate resources, technical support, and system compatibility directly influence usage behavior. Alalwan et al. (2017) found that better perceived infrastructure support increases mobile banking usage frequency and intensity. Habit is the degree to which behaviors are performed automatically due to prior learning. Venkatesh et al. (2012) observed that habitual users act without deep cognitive effort. Tak and Panwar (2017) confirmed that stronger habits predict more consistent mobile banking use, often surpassing behavioral intention. Behavioral intention is the primary predictor of actual usage. Chao (2019) demonstrated that stronger intentions lead to higher frequency and consistency in technology-based self-service use. Age affects technology interaction patterns. Oechslein et al. (2014) found younger users exhibit higher frequency, more exploratory behavior, and greater willingness to adopt new features than older users.

Experience reflects the length and intensity of technology use. Venkatesh et al. (2012) explained that experience promotes internalization of technology behaviors. Tarhini et al. (2016) showed experienced users demonstrate more sophisticated, engaged, and advanced usage patterns in e-learning contexts. Gender influences adoption and usage patterns. Wong et al. (2020) found males use utilitarian applications more frequently, while females prefer social and communication-oriented features, affecting both usage intensity and type.

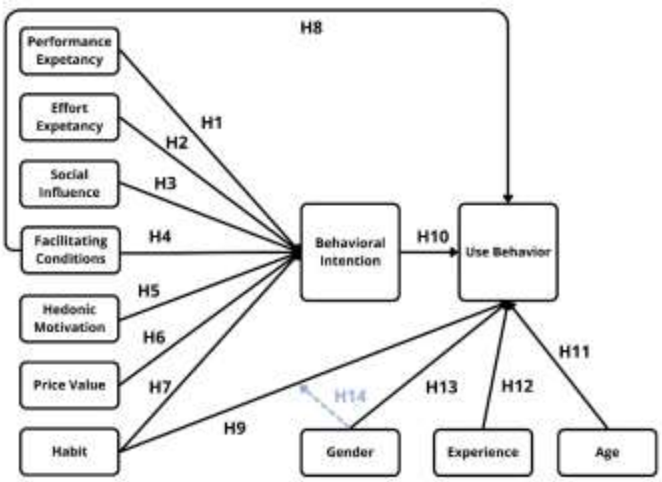
H8: Facilitating conditions has a significant effect on use behavior.
H9: Habit has a significant effect on the use behavior.
H10: Behavioral intention has a significant effect on use behavior.
H11: Age has a significant effect on use behavior.
H12: Experience has a significant effect on use behavior.
H13: Gender has a significant effect on use behavior.

2.4. Gender as Moderating Variable

The moderating effect of gender on the relationship between habit and use behavior suggests that the strength of habitual influence on actual technology usage may differ between males and females. Venkatesh et al. (2012) in the UTAUT2 model proposed that gender moderates the effect of habit on use behavior, indicating that the automaticity of behavior developed through repeated use may manifest differently across genders. This moderation effect can be attributed to differences in cognitive processing, decision-making styles, and the extent to which males and females rely on routinized behaviors when interacting with technology (Giua et al., 2022; Bi & Zou, 2024). Use behavior reflects actual engagement, measured by frequency and reliance on the app for core activities. In Indonesian shrimp farming, fostering habit through consistent use could bridge low active user rates, as internal data suggest (Mira et al., 2022). The habit dual role underscores the need for designs that encourage repetition, aligning with studies on digital transformation in primary sectors (Nikolopoulou et al., 2020).

Recent empirical studies provide support for this moderating relationship. Chen et al. (2024) in their study of AI chatbot adoption for tourism found significant gender differences in technology usage patterns, with males showing stronger reliance on habitual behaviors in their technology use compared to females. Similarly, research by Xu et al. (2024) examining Chinese university educators' acceptance of AI tools demonstrated that while habit emerged as the strongest predictor of actual usage behavior, the strength of this relationship varied across gender groups, with males exhibiting more pronounced habitual usage patterns once routines were established.

H14: Gender moderates the relationship between habit and use behavior.



Source: Ventakesh et al. (2012)
Figure 1. Conceptual Framework. UTAUT2 Theory Model Picture

The design of the relationship between variables is presented in Figure 1**,** which is the basis for the formulation of the following research hypothesis. This study uses the UTAUT2 framework as the basis for the development of a research model. The framework describes the relationship between the UTAUT2 construct, the intention of use, and the behavior of using digital applications by small- and medium-scale farmers (Ventakesh et al, 2012).

3. Methods

This study employs a quantitative survey to examine factors influencing the adoption of the JALA App by shrimp farmers, focusing on small- to medium-scale operators managing 1–10 aquaculture ponds. The population includes all such *vannamei* shrimp farmers familiar with digital pond management applications, from which 140 respondents were purposively selected to ensure direct experience with the technology. A structured questionnaire consisting of 30 statements scored on a 5-point Likert scale (1 being strongly disagree and 5 being strongly agree) was used to gather data. The questionnaire was delivered both offline through direct interviews and online through Google Forms. Respondent selection used purposive sampling based on JALA App usage frequency in the past three months (routine vs. non-routine) and user role (owner, technician, or admin), ensuring relevance to actual technology use (Campbell et al., 2020). These criteria were only for sample selection, keeping respondents homogeneous for model testing.

Purposive sampling is suitable for accessing groups with direct experience relevant to research objectives. Sample size followed PLS-SEM guidelines, requiring at least ten times the number of indicators in the largest construct. With four indicators in the most complex construct, the minimum was 40 respondents; 140 respondents exceeded this requirement, ensuring sufficient statistical power (Hair et al., 2014; Ong et al., 2023). The research model is based on UTAUT2, linking performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit to behavioral intention and use behavior (Venkatesh et al., 2012). Although UTAUT2 typically includes moderators such as age, gender, and experience, this study focuses on direct determinants of adoption, recording demographics for descriptive analysis.

The model is relevant as it captures relationships between perception, motivation, and technology use in primary production sectors like aquaculture (Fox et al., 2018; Wang et al., 2023; Cimino et al., 2024). Previous studies in agriculture and livestock show that UTAUT2 effectively explains small-scale operators' adoption of digital technologies, including smart farming systems and mobile applications, making it suitable for analyzing JALA App adoption. Partial Least Squares Structural Equation Modeling (PLS-SEM), which was selected for its ability to handle complex models, tolerance to non-normal data, and efficacy with small to medium samples, was used to analyze the data. Analysis included measurement and structural model evaluation (Hair, 2014; Russo & Stol, 2021; Angelina et al., 2024). Convergent validity was assessed via outer loadings (≥0.70) and AVE (≥0.50), while discriminant validity was assessed using Fornell-Larcker and cross-loading analysis. Reliability was tested using Composite Reliability (CR) and Cronbach's Alpha (≥0.70), with CR preferred for flexibility in indicator weighting (Purwanto & Sudargini, 2021). The structural model tested causal relationships using bootstrapping to obtain path coefficients, t-statistics, and p-values (significant if $p < 0.05$ or $t > 1.96$). R-Square (R^2) measured explained variance, while Q-Square ($Q^2 > 0$) assessed predictive relevance, confirming the model's ability to explain and predict adoption behavior of the JALA App among small- and medium-scale shrimp farmers.

4. Results

Table 1 summarizes the characteristics of the 140 small- to medium-scale *vannamei* farmers who had known or used the JALA App. Most respondents were men (70.7%), with a productive age range of 25–35 years (54.3%). In terms of their role in the pond, the majority were pond owners (39.3%) and technicians (28.6%), directly involved in the management process. Most respondents had 2–4 years of cultivation experience (50.7%), followed by those with more than 4 years of experience (32.9%). In terms of pond management, most respondents managed 2–4 ponds (79.3%), with three ponds being the most common number managed (33.6%). Regarding technology utilization, the majority used the JALA App occasionally to often (2–6 times per week), reflecting active engagement, though it is not yet fully integrated into their daily routine.

Table 1. Characteristic Respondent

Construct	Criteria	Frequency	Percentage (%)
Gender	Man	99	70.7%
	Woman	41	29.3%
	Total	140	100%
Age	< 25 years old	12	8.6%
	25 – 35 years old	76	54.3%
	36 – 45 years old	39	27.9%
	> 45 years old	13	9.3%
	Total	140	100%
Role in the Pond	Pond Owner	55	39.3%
	Technician	40	28.6%
	Pond Manager	18	12.9%
	Kids Pool	18	12.9%
	Admin / Pond Laboratory	9	6.4%
	Total	140	100%

Construct	Criteria	Frequency	Percentage (%)
Long Experience	< 2 Years	23	16.4%
	2 – 4 Years	71	50.7%
	> 4 Years	46	32.9%
	Total	140	100%
Number of Pools	1	9	6.4%
	2	33	23.6%
	3	47	33.6%
	4	31	22.1%
	5	20	14.3%
	Total	140	100%
Frequency of Use of JALA	Never	9	6.4%
	Rarely (1 time/week or less)	33	23.6%
	Sometimes (2-3 times/week)	47	33.6%
	Frequent (4-6 times/week)	31	22.1%
	Daily (7 times/week or more)	20	14.3%
	Total	140	100%

The elements and indicators of the UTAUT2 model used to evaluate users' adoption of the JALA App are listed in Table 2. Performance expectancy, effort expectancy, social influence, price value, habit, behavioral intention, and use behavior are all included in the model. The usefulness, convenience of use, social support, cost-benefit value, regular use, intention to continue, and actual usage of the app are all measured by particular indicators that correspond to each concept. All things considered, the table outlines the operational variables that are used to assess the elements that affect the adoption and ongoing use of the JALA App.

Table 2. Constructs and Research Indicators

Construct	Code	Indicators
Performance Expectancy (PE)	PE1	JALA App helps increase pond management productivity
	PE2	JALA App Improves efficiency in monitoring pond water quality
	PE3	JALA App makes it easier to manage feed and cultivation products
	PE4	JALA App Makes it Easy to Predict Crop Yields
Effort Expectancy (EE)	EE1	JALA App is easy to use and learn
	EE2	Feel comfortable using it in daily activities
	EE3	Doesn't require a lot of effort/difficulty
	EE4	Features are easy to access and understand
Social Influence (SI)	SI1	People around recommend using JALA App
	SI2	Support from important people in the use of the JALA App
Facilitating Conditions (FC)	FC1	Have the resources to use the JALA App
	FC2	Technical support available
	FC3	Hardware/software supports usage
	FC4	Able to use the JALA App independently
Price Value (PV)	PV1	The cost is commensurate with the benefits obtained
	PV2	Provides good value for money
	PV3	Subscription fees according to profits
Habit (HT)	HT1	Used to using the JALA App for pond monitoring
	HT2	Using the JALA App automatically
	HT3	Become part of the daily routine in farm management
	HT4	Feeling lost if you don't use the JALA App
Behavioral Intention (BI)	BI1	Intend to continue using the JALA App
	BI2	Intend to continue using the JALA App

Construct	Code	Indicators
	BI3	Plan to increase the use of the JALA App in the future
Use Behavior (UB)	UB1	Frequency of use of JALA App
	UB2	Using the JALA App when monitoring the condition of the pond
	UB3	Relying on the JALA App as the main tool for shrimp farming

In order to assess the validity and reliability of the latent construct in comparison to the observed indicators, the outer model was evaluated. The analysis's findings demonstrated that the total outer loading value was over 0.70, indicating that the convergent validity requirements had been satisfied. The Average Variance Extracted (AVE) result, which completely surpassed the minimal barrier of 0.50, further reinforced the convergent validity. In addition, construct reliability is tested through Composite Reliability (CR) values, specifically using rho_c values, which are recommended as the primary measure of reliability in the PLS-SEM approach. All constructs have a CR value above 0.70, which indicates good internal reliability (Purwanto & Sudargini, 2021). Discriminant validity testing has also been met based on the Fornell-Larcker and HTMT criteria (< 0.90), which show that each construct has adequate discrimination against the other (Hair, 2014).

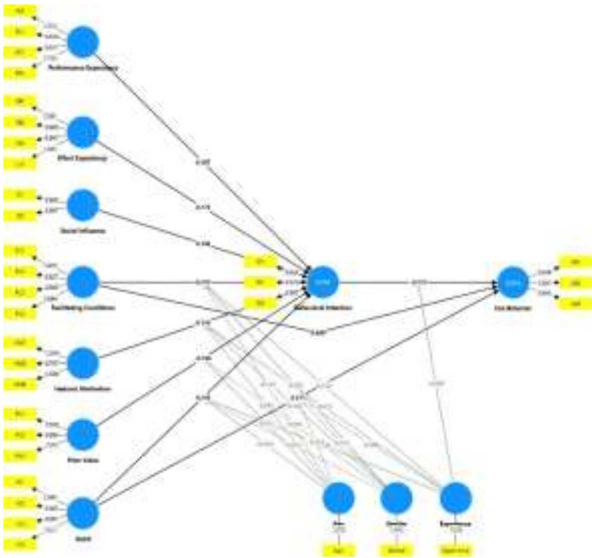


Figure 1. Visualization of the Outer Model of PLS-SEM

Figure 2, a representation of the outer model, illustrates how the latent construct and the observed indicator are related. PLS-SEM results' outer model, which illustrates the connections between latent constructs and their observed indicators. Performance expectancy, effort expectancy, social influence, price value, habit, behavioral intention, and use behavior are among the constructs that are linked to their indicators by means of substantial loading values. The model demonstrates how these dimensions interact, specifically demonstrating how behavioral intention mediates the impact of other factors on JALA App use behavior.

Table 3 presents the outer loading values of each indicator for its corresponding construct. All loading values exceed the acceptable threshold of 0.7, indicating good indicator reliability and validity. It is evident from this that each indication, including behavioral intention, effort expectancy, facilitating conditions, hedonic motivation, habit, performance expectancy, price value, social influence, and use behavior, is a robust representation of its hidden construct. that every measurement item is credible and valid for determining the variables affecting JALA App usage. In addition, the construct reliability and convergent validity tests are also displayed through CR and AVE values.

Table 3. Value of Outer Loading Indicator to Construct

Construct	Indicator Code	Outer Loading
Behavioral Intention	BI1	0.824
	BI2	0.839
	BI3	0.867
Effort Expectancy	EE1	0.881
	EE2	0.809
	EE3	0.847
	EE4	0.841
Facilitating Conditions	FC1	0.809
	FC2	0.827
	FC3	0.869
	FC4	0.844
Hedonic Motivation	HM1	0.869
	HM2	0.797
	HM3	0.848
Habit	HT1	0.843
	HT2	0.883
	HT3	0.901
	HT4	0.822
Performance Expectancy	PE1	0.825
	PE2	0.836
	PE3	0.837
	PE4	0.793
Price Value	PV1	0.868
	PV2	0.890
	PV3	0.852
Social Influence	SI1	0.860
	SI2	0.897
Use Behavior	UB1	0.944
	UB2	0.931
	UB3	0.969

Table 4. Value of Outer Loading Indicator to Construct

Variable	Composite Reliability (CR)	Average Variance Extracted (AVE)
Behavioral Intention	0.881	0.711
Effort Expectancy	0.909	0.713
Facilitating Conditions	0.904	0.701
Habit	0.921	0.745
Hedonic Motivation	0.877	0.703
Performance Expectancy	0.893	0.677
Price Value	0.903	0.757
Social Influence	0.871	0.772
Use Behavior	0.964	0.899

To evaluate the model's predictive power on endogenous constructs and investigate the relationship between its constructs, a structural model evaluation was conducted. The two main indicators used in the inner evaluation of this model are the R-Square (R^2) to measure the proportion of endogenous construct variance that can be explained by the exogenous construct, and the Q-Square (Q^2) used to assess the predictive relevance of the model (Kock, 2018).

Based on the results of the analysis in Table 5, the behavioral intention construct has an R^2 value of 0.793, which means that 79.3% of the variation in behavior intention can be explained by the exogenous construct in the model. Meanwhile, the use behavior construct has an R^2 value of 0.416, which indicates that the model can explain 41.6% variation in use behavior. This R^2 value indicates excellent predictive ability for behavioral intention and moderate for use behavior.

Additionally, the predictive relevance of the model to endogenous factors is assessed using Q-Square (Q^2) testing. Table 5 shows that the model has good predictive relevance to behavior intention, with a Q^2 value of 0.473 for behavioral intention. Meanwhile, the Q^2 value for use behavior is 0.299, which still shows decent predictive relevance, albeit slightly lower (Hair, 2014).

Table 5. Value of Outer Loading Indicator to Construct

Endogenous Constructs	R-Square (R^2)	Q-Square (Q^2)
Behavioral Intention	0.793	0.473
Use Behavior	0.416	0.299

As a result, the model's internal evaluation findings validate that it has good predictive relevance and sufficient predictive power for the endogenous variables, behavioral intention and use behavior. To examine the importance of routes in structural models, bootstrapping was used to provide estimates of the t-statistic and p-value. The association between the model's constructs is statistically significant if the t-value is larger than 1.96 and the p-value is less than 0.05. Table 6 presents the results of the path coefficient test, with t-statistics and p-values indicating the significance of most of the relationships between the constructs (Hair et al., 2019).

Table 6. Hypothesis Testing

Relationship	β (Original Sample)	t-statistic	p-value	Decision
OR → BI	0.107	1.980	0.048	Significant
EE → BI	0.279	3.892	0.000	Significant
SI → BI	0.198	2.896	0.004	Significant
FC → BI	0.247	3.446	0.001	Significant
HM → BI	0.176	2.093	0.036	Significant
PV → BI	-0.196	3.068	0.002	Significant (neg)
HT → BI	0.249	3.137	0.002	Significant
FC → UB	0.460	3.612	0.000	Significant
HT → UB	0.473	3.110	0.002	Significant
BI → UB	-0.237	1.528	0.127	Insignificant
Age → UB	-0.027	0.199	0.842	Insignificant
Experience → UB	0.027	0.206	0.837	Insignificant
Gender → UB	-0.104	1.622	0.105	Insignificant
Gender × Habit → UB	0.214	2.318	0.020	Significant

Based on the results in Table 6, most relationships among the main constructs of the UTAUT2 model were statistically significant ($p < 0.05$). Effort expectancy, facilitating conditions, habit, and social influence positively and significantly affected behavioral intention, while habit also had a strong effect on use behavior. These findings indicate that perceived ease of use, adequate technical support, habitual use, and social influence play key roles in encouraging farmers to adopt the JALA App. However, the link between behavioral intention and use behavior was insignificant ($p > 0.05$), suggesting that farmers' intentions have not consistently translated into real usage. This gap may stem from external barriers such as limited time, inadequate infrastructure, or persistent manual practices in shrimp farming. These results collectively provide evidence for answering the third research question, showing that the UTAUT2 model can explain adoption patterns in this farmer segment, with habit and facilitating conditions emerging as the most influential drivers of real usage behavior.

5. Discussion

This section interprets the research results presented earlier, elaborating them thematically to explain why shrimp farmers decide to use or refrain from using the JALA application. The study's primary finding was the insignificance of the relationship between behavioral intention and usage behavior ($p = 0.127$). This contrasts with findings from several meta-analyses that typically identify the behavioral intention on usage behavior relationship as one of the most robust predictors. This phenomenon, known as the intention–behavior gap, indicates that having positive intentions alone does not guarantee consistent use of the application in daily work routines (Tamilmani et al., 2021; Blut et al., 2022). In line with prior studies suggesting that workers or farmers often require support and training to enhance technology adoption motivation, this research confirms that habits and facilitating conditions play more dominant roles (Setyono et al., 2025).

The study identified habit ($\beta = 0.473$) and facilitating conditions ($\beta = 0.460$) as the two strongest determinants of actual usage. The significant impact of habit aligns with research on technology that involves repeated use, such as mobile phone usage among students (Cimino et al., 2024). This suggests that automatic behaviors or well-established routines, rather than deliberate, intention-based decision-making, are what motivate JALA adoption. Similarly, the powerful influence of enabling conditions highlights the necessity of appropriate technical skills and proper infrastructure, including reliable internet connectivity and mobile device access, for real-world deployment in the field.

Regarding intention formation, effort expectancy, or the perception of ease of use, emerged as the strongest factor ($\beta = 0.279$). Interestingly, this finding contrasts with several meta-analyses that show a weakening influence of effort expectancy for widely familiar technologies. For shrimp farmers with limited time and digital literacy, the perception that JALA is simple and user-friendly becomes a decisive motivator for adoption. Conversely, performance expectancy, or perceived usefulness, though significant, exhibited a smaller effect ($\beta = 0.107$). This suggests that even if farmers believe the application is beneficial, they are unlikely to adopt it if it is difficult to use. Hence, intuitive and accessible design takes precedence over having a large set of features. This aligns with Yeo and Keske (2024), who argue that in digital agriculture, perceived economic benefits will not be realized if the technology demands high technical skills or operational complexity.

A particularly unexpected finding was the significant negative effect of price value on behavioral intention ($\beta = -0.196$). Contrary to theoretical expectations where favorable value perceptions should enhance intent this suggests that the freemium model may generate unintended perceptions. In JALA's case, the availability of free features may be interpreted by farmers as a signal of lower quality or restricted functionality. Consequently, users who focus on the "price" dimension (i.e., free usage) may become less motivated to use it seriously. This is consistent with Hamari et al. (2017), who observed that when free services already deliver adequate value, introducing premium features may not significantly increase perceived worth.

Furthermore, the study found no significant moderating effects of age, gender, or experience on behavioral intention. While some previous studies identify demographic variations as influential, this research indicates otherwise. A plausible explanation is that the challenges of shrimp farming such as disease management and feed optimization are universal among farmers, thereby neutralizing demographic differences. As a result, usability and perceived benefits of the JALA application remain equally relevant to all user groups (Wu & Liu, 2023).

The practical implications of this study highlight three key strategies for enhancing the adoption and effective utilization of the JALA App. First, in terms of user behavior, developers should integrate the application into farmers' daily workflows by optimizing repetitive processes such as feed logging and water quality monitoring. Second, concerning user experience, developers must reduce cognitive barriers through contextual guides, interactive tutorials, and in-app glossaries explaining technical terms, thus empowering users to explore advanced features confidently. Third, in pricing strategy, developers should introduce flexible subscription options such as per-cultivation-cycle plans to align perceived value with actual costs. Collectively, these implications can strengthen user engagement, satisfaction, and long-term commitment to JALA, advancing technology-driven efficiency in the aquaculture sector.

6. Conclusion

The findings of this study reveal that shrimp farmers' adoption and continued use of the JALA App are predominantly influenced by habit and facilitating conditions. These two factors play the most decisive roles in determining actual usage behavior, indicating that repeated routines and adequate infrastructure are essential for consistent technology utilization. Meanwhile, effort expectancy, social influence, hedonic motivation, and price value significantly shape behavioral intention, with ease of use proving more critical than perceived usefulness (performance expectancy, performance expectancy. This highlights that farmers prioritize practicality and time efficiency over the breadth of features. The insignificance of the behavioral intention on usage behavior relationship ($p = 0.127$) further demonstrates the presence of an intention–behavior gap, where positive attitudes do not automatically translate into real adoption unless supported by habits and facilitating conditions.

This study confirms that in contexts such as aquaculture, where tasks are highly repetitive and time-constrained, technology adoption is better explained by behavioral automaticity rather than cognitive intention alone. The negative relationship between price value and behavioral intention also provides new insight into freemium model dynamics, suggesting that free access can sometimes reduce perceived quality, discouraging serious engagement. These findings contribute to a deeper understanding of digital transformation in traditional sectors, where usability, habit formation, and affordability must align to drive sustainable adoption.

Practical implications suggest that developers should focus on making JALA an integral part of farmers' daily routines by simplifying workflows, automating repetitive inputs, and enhancing user friendliness through intuitive design, short tutorials, and contextual help features. Flexible pricing plans such as per-cultivation-cycle subscriptions can also improve perceived value and encourage broader use. Because this study used a cross-sectional methodology, its limitations and potential directions for future research are mainly methodological. To monitor behavioral changes over time and across locations, future research should use comparative and longitudinal methodologies. To improve predicting accuracy, characteristics like perceived risk and trust should be included.

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The data that support the findings of this study are available from the corresponding author upon reasonable request.