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Examining small farm holders' adoption intention on artificial intelligence of things for sustainable agriculture in developing country: A structural equation modelling assessment

Alexander A. Hernandez[1]*, Suchita Manajit[2], Jessa Frida T. Festijo[3], Jennifer D. Tucpi[4]
[1]Information Technology Department, College of Technology, Lyceum of the Philippines University, Manila, Philippines; alexander.hernandez@lpu.edu.ph (A.A.H.).
[2]Walailak University International College, Walailak University, Nakhon Si Thammarat, Thailand.
[3]Research and Innovation Center, Lyceum of the Philippines University, Manila, Philippines.
[4]Academic Affairs Office, Lyceum of the Philippines University, Manila, Philippines.

Abstract: Artificial Intelligence of Things (AIoT) plays a crucial role in promoting sustainable farming and enhancing productivity. This emerging technology is increasingly adopted in developed countries; however, it remains under investigation in developing nations due to its novelty, contextual challenges, and support factors. Consequently, the adoption rate among farmers with small holdings is relatively low. This study addresses this research gap by developing an extended framework based on the Unified Theory of Acceptance and Use of Technology (UTAUT), incorporating perceived gains and sustainability factors to provide a comprehensive understanding of farmers' adoption intentions. The analysis employs measurement and structural models using Partial Least Squares Structural Equation Modeling (PLS-SEM). Results indicate that performance expectancy, effort expectancy, social influence, trust, and government support significantly influence the intention to adopt AIoT. Conversely, facilitating conditions and price value were found to be insignificant. Moreover, perceived gains and sustainability-related factors exert the most substantial impact on the intention to use AIoT among small farm holders, suggesting that these farmers have a positive attitude towards adopting AIoT for smart and sustainable agricultural practices, particularly in the Philippines.

Keywords: *Artificial intelligence of things, Artificial intelligence, Developing country, Small farm holders, Sustainable agriculture.*

1. Introduction

Agriculture is a sector in developing countries that contributes to gross domestic product. At present, agriculture output accounts for 50% to 60% in the Philippines, Thailand, and Indonesia, respectively [1]. Although agriculture has overgrown at some time, it still suffers problems due to inaccessibility and expensive integration of emerging technologies such as artificial intelligence and internet of things to enhance throughput and productivity [2, 3]. Also, a decline in the agriculture sector's performance is affecting the stability of the supply chain in developing countries, such as Thailand, the Philippines, and Indonesia. As a result, the prices of basic commodities are getting more expensive. While there is a decline, farmers' shortages happen as they experience increasing farming expenses, insufficient farming support, and changes in employment priority from farming to non-farming for better salaries [4]. As these problems continue to exist, at this technologically enabled period, developing countries are trying to cope with agricultural challenges using artificial intelligence, the Internet of Things, and blockchain, among others [5].

More recently, artificial intelligence of things (AIoT) is progressively adopted for smart agriculture to enable technology assisted farming practices in developing countries [6]. First, AIoT is adopted in

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* Correspondence: alexander.hernandez@lpu.edu.ph

developed countries as mature infrastructure and availability of devices to build AIoT systems and implement it Sharma, et al. [7]. However, there are limited studies investigating sustainability and climate-change related factors to provide in-depth understanding for its present contextual relevance to developing countries evidently suffering from this climate vulnerability and resource constraints [8]. Second, the Philippines, as a developing country with strong reliance on agriculture, needs to be investigated, as it presents a unique case for studying AIoT adoption as agriculture is one of the most climate sensitive sectors in the Philippines, and other developing countries due to climate change and serious disaster experience. Third, small farm holders' intentions to use AIoT, is not as much explored, making it unclear to determine their reception of this innovative solution to smart farming adoption.

This study develops an extended unified theory of acceptance and use of technology (UTAUT) model on the adoption intention-based literature and survey data analyzed through partial least squares and structural equation modeling (PLS-SEM). By considering the research gaps, the study contributes by providing evidence of adoption intention with consideration of sustainability (green) and perceived gain-related factors, to uncover the relationships and significance of the factors under investigation for small farm holders in the Philippines and other developing countries.

The paper follows a structured format, comprising literature review, hypothesis development, materials and methods, results discussion, conclusion and future work.

2. Literature Review

Artificial Intelligence of Things (AIoT) is an emerging technology for smart agriculture. It combines the capabilities of Artificial Intelligence (AI) with the Internet of Things (IoT) [9]. In relation to agriculture, AIoT uses IoT devices to collect environmental data such as soil moisture, temperature, and humidity, among others, complemented by the AI algorithms as applied to analyzing data and making real-time decisions or predictions [10], (e.g., optimizing fertilizer use, irrigation scheduling, predicting infestation outbreaks, smart harvesting, and supply chain management) [11, 12]. Thus, AIoT is a broader concept that focuses on intelligence in interconnected devices that increasingly plays an important role in smart (sustainable) agriculture.

Previous studies were conducted to determine the factors influencing the adoption intention of AIoT for smart farming in developing countries. In a recent study, AIoT was explained by providing evidence of adoption intention for crop management, specifically growth monitoring and yield production [13]. Results show that there is moderate to high acceptance of AIoT based on the performance expectancy, effort expectancy, facilitating conditions, cost, and price value. Similarly, a recent study suggests that usefulness, ease of use, cost, and support from the government are crucial factors for its use and continuance, leading to sustainable agricultural conditions. Further, another study found that perceived usefulness, institutions as contextual factors, and social influence play a significant role in the adoption of climate smart agriculture technologies [14]. On the other hand, there are a few studies that examine the influence of cost of investments and targeted price of the crops, sustainability, and climate-related factors when using AIoT for smart agriculture and precision farming practices, in developing countries [15].

In this paper, information systems models and theories were considered such as the unified theory of acceptance and use of technology (UTAUT). The UTAUT focuses on aspects of performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation [16]. The UTAUT was chosen as it provides a comprehensive framework that focuses on use intention and behavior, predictive capability for emerging technologies [17], and relevance to the context of introducing AIoT in agriculture, especially the complex settings and nature of small farm holders in developing countries.

Several studies proposed an extended UTAUT model that considers technological and non-technological factors to explain the acceptance or rejection of individuals to new technologies [18]. Another study considered developing an extended UTAUT model by highlighting the crucial role of effort expectancy, performance expectancy, facilitating conditions, hedonic motivation, government support, price value, personal innovativeness, and trust as significant factors to the adoption intention of IoT for agriculture in Bangladesh [19]. Similarly, another study investigated the intention to use ICTs in agriculture's productivity in Zambia and found that performance expectancy, facilitating conditions, effort expectancy, and social influence had a positive relationship with intention [20]. However, there is a dearth of studies explaining sustainable and perceived gain factors related to AIoT adoption intention and use in developing countries, such as the Philippines. Thus, this research aims to address these research gaps.

2.1. Hypothesis Development

Performance expectancy is the extent to which an individual believes that an emerging technology can achieve his or her task or goal and reach productivity. Previous studies found that performance expectancy positively impacts adoption intention in artificial intelligence in smart agriculture [19, 21]. Further, a recent study found that the use of the Internet of Things was found effective and assisted in productive smart farming decisions [22]. In another study, performance expectancy contributes to the use behavior of IoT in agrotourism in Malaysia [23]. When performance expectancy is positively perceived by small farm holders (SFHs) in AIoT for sustainable agriculture, it will more likely be adopted. As a result, this study proposes the hypothesis that:

H_1: Performance expectancy has a positive significant impact on the AIoT adoption intention in SFHs.

Effort expectancy is the level of convenience and user-friendliness that individuals feel when using an information system [24]. Prior studies suggest that effort expectancy contributes to adoption intention and continuance of emerging technologies [25]. In a recent study, it was found that effort expectancy, network prominence, and environmental uncertainty, which led to use and continuance of digital platforms for sustainable and successful agricultural ecosystems [26]. This present study operationalizes effort expectancy as the convenience and user-friendliness that small farm holders perceive about AIoT. As a result, this study proposes the hypothesis that:

H_2: Effort expectancy has a positive significant impact on the AIoT adoption intention in SFHs.

Social influence is the extent to which an individual believes that important others believe that he or she should use a new system [27]. A recent study suggests that peers and friends' experience contribute to the adoption intention and use of intelligent hog farming technology [28]. Besides, peer reviews and satisfaction were noted as influential to convince farmers to try artificial intelligence to enhance farming productivity and reduce monitoring challenges [29]. On the contrary, a study presents the insignificance of social influence on the intention to adopt IoT for farming [30]. This study operationalizes the social influence of farmers related to AIoT [31]. When farmers receive positive reviews from farming peers, AIoT will be more likely adopted. As a result, this study proposes the hypothesis that:

H_3: Social Influence has a positive significant impact on the AIoT adoption intention in SFHs.

Facilitating conditions refer to the extent to which technical structure and organizational resources are available to support the use of an emerging system [27]. Previous studies found that technical infrastructure such as connectivity, weather information stations, cloud computing, and sensors [32]. A recent study found that facilitating conditions contribute to the positive intention, use, and continuance of artificial intelligence and internet of things for smart farming [33]. Similarly, facilitating conditions were a significant contributor [34]. This study operationalizes facilitating conditions as the essential infrastructure such as connectivity, IoT sensors, weather information station, and mobile applications are available to pursue AIoT for smart agriculture. When these facilitating conditions are made available, individuals engaged in smart farming will have positive intention and use behavior. As a result, this study proposes the hypothesis that:

H_4: Facilitating conditions has a positive significant impact on the AIoT adoption intention in SFHs.

Price value refers to the cost of adopting AIoT solutions and the value or return that these AIoT bring to sustainable and smart agriculture [35]. Previous studies found price value's significance in adoption intention and use behavior [36, 37]. Similarly, another study found that price value contributes to positive acceptance of AI and IoT for smart farming practices [38]. Besides, when benefits derived from AIoT investments justify its costs, SFHs will likely adopt and continue to use AIoT. As a result, this study proposes the hypothesis that:

H_5: Price value has a positive significant impact on the AIoT adoption intention in SFHs.

Trust refers to the confidence or reliance in a specific technology. When AIoT can confidently deliver its promises for green and sustainable agriculture, small farm holders will likely adopt it [39]. Previous studies have established a positive association between trust and behavioral intention in smart agriculture and precision farming [40, 41]. Moreover, a recent study found that trust is a vital factor in the adoption of smart farming technology [42]. In addition, another study suggests that trust has a significant link with use behavior on climate-smart agriculture in most countries investigated [43]. As a result, this study develops the hypothesis that:

H_6: Trust will have significant positive impact on the AIoT adoption intention of small farm holders.

Government Support refers to the government's climate adaptation programs to support green and lean practices leading to sustainability [44]. Previous studies found that climate adaptive programs for smart agriculture positively affect adoption intention [45]. Previous studies emphasized the government's significant contribution to a positive acceptance of IoT for smart agriculture [46]. Similarly, individuals who received sufficient support from the government continue to adopt artificial intelligence for smart farming [32]. This study operationalizes support for promotion and training, guidelines, and infrastructure to encourage adoption of AIoT for smart agriculture. When there is government support available to adopt emerging technologies, SFHs will likely adopt AIoT for sustainable agriculture. As a result, this study proposes the hypothesis that:

H_7: Government support will have a significant positive impact on the AIoT adoption intention of small farm holders.

Resource Conservation is the perception of small farm holders that artificial intelligence of things offers financial benefit through using fewer resources. Previous studies found that the internet of things and artificial intelligence allow farmers to conserve water usage [47] through real-time data in scarce areas, and reduce reliance on irrigation facilities, applying fertilizers more efficiently, preventing wastage [48, 49] could lead to resource conservation [50, 51]. When small farm holders perceive that AIoT could result in resource conservation, it will more likely be adopted and considered a gain. Thus, this study proposes the hypothesis that:

H_8: Resource conservation will have a positive significant impact on the AIoT adoption intention of small farm holders.

Operating Cost is the belief that using AIoT for smart agriculture will save operating expenditures. Previous studies found that AIoT can reduce farming operations by automating repetitive tasks, reducing labor costs, and human errors [52, 53]. In a recent study, artificial intelligence and the internet of things were used for real-time monitoring and data-driven decisions [54], resulting in reduced operating costs and downtime of farm operations [55]. When small farm holders perceive that AIoT can result in operating cost savings, it will more likely be adopted for sustainable agriculture and farming activities. As a result, this study proposes the hypothesis that:

H_{9}: Operating cost saving will have significant positive impact on the AIoT adoption intention of small farm holders

Increased Production is the expectation that using AIoT will increase the productivity of the farm. Previous studies suggest that artificial intelligence and the internet of things play a vital role in sustainable agriculture [56]. In a recent study, it was found that artificial intelligence with IoT can result in crop yield of small farm holders by forty percent (40%) [57]. Similarly, another study suggests that by using AIoT, a projected 30% is expected to generate greater profitability with the same resources for small farm holders' productivity and growth in business. When small farm holders perceive that AIoT could lead to increased production of farms, it will more likely be adopted. As a result, this study proposes the hypothesis that:

H_{10}: Increased production will have significant positive impact on the AIoT adoption intention of small farm holders

Eco-Friendly farming refers to the expectation that using AIoT will promote environmentally friendly farming practices and reduce its environmental impact. Previous studies suggested that the internet of things combined with artificial intelligence can help minimize the environmental impact of farming practices [58]. On the other hand, studies found that its combination introduces new approaches to protecting the natural resources used or surrounding farms [59, 60]. As a result, these innovations can make farming sustainable for future generations. Hence, this study proposes the hypothesis that:

H_{11}: Eco-Friendly Farming will have significant positive impact on the AIoT adoption intention of small farm holders.

Energy Efficiency refers to the expectation that AIoT based equipment and agricultural machinery with optimized algorithms, through solar-based AIoT devices, can reduce energy usage in farming operations [61, 62]. Previous studies found that IoT and AI introduced energy-efficient practices are vital for greening and sustainable agriculture [63]. A recent study found that energy-efficient IoT and AI applied to agriculture can result in cost-effective and eco-friendly farming practices [64]. When small farm holders perceive that AIoT for agriculture promotes energy efficiency, it will be more widely adopted. Thus, this study suggests that hypothesis that:

H_{12}: Perceived Energy Efficiency will have significant positive impact on the AIoT adoption intention of small farm holders.

Behavioral intention refers to the individual's relative strength of intention to perform a behavior in the near future. Previous studies found that an individual's motivation can predict acceptance and continuance of use of new technology. In this study, the intention to use AIoT is measured.

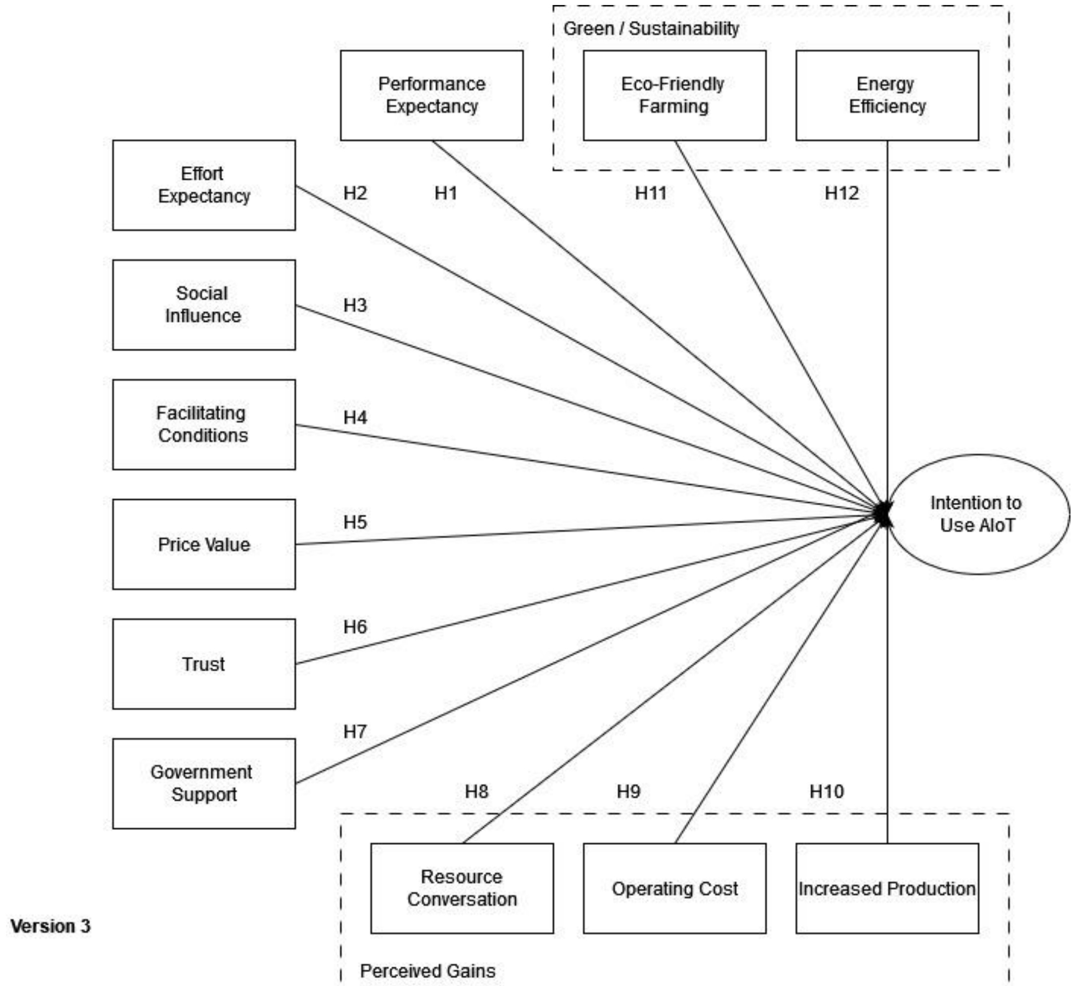

Figure 1.
Conceptual Framework on AIoT adoption intention in SFHs.

3. Materials and Methods

The survey instrument was developed based on the conceptual framework developed with prior studies as a source of survey questions. The survey items were modified to consider the current context of small farm holders and smart agriculture. The survey was structured with two parts covering (1) profile of the respondents and (2) adoption intention questions. The survey has 39 items covering adoption intention question items on performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), price value (PV), trust (TR), government support (GS), eco-friendly farming (EF), energy efficiency (ENR), resource conservation (RC), operating costs (OC), increased production (IP), and intention to use (ITU). The survey uses a 7-point Likert's scale to determine the agreement or disagreement of respondents for survey items, from strongly disagree (1) to strongly agree (7). Initially, the survey was deployed to 50 respondents to check their understanding of the questions. Further, the survey was also reviewed by technology adoption research experts. Comments and suggestions were reflected in the revised survey. The final survey version was created in Google Forms, to provide ease of access and deployment to the respondents' email, text messages, and social media accounts.

This study applies purposive sampling of small farm holders in the Philippines. The farmers were from different provinces such as Regions 2, Region 3, Region 4A-4B, Region 5, and Region 6. Purposive sampling is applicable as these SMFs have agricultural contributions, understand resource constraints and efficiency, need support for agriculture as they are vulnerable to climate change and environmental risks, localized farming practices, and can drive crop productivity and reduce poverty. Local government units and agriculture offices were contacted to determine the small farm holders in these regions. After such, the SFH were contacted through their registered mobile numbers via call or text messages. To comply with ethics in research, an invitation to participate in the survey was sent to the respondents, and confirmed participants were stored in a secured Google Sheet as a reference for the deployment of the survey. Also, informed consent was provided to the participants to ensure adherence to ethics in research.

The survey was deployed through the SFHs' contact number, email, and social media accounts in October - November 2024. The survey turnout was 78% (n = 446) from the confirmed respondents. From this number, all 446 completed responses were used for modeling and analysis. For this study, Smart PLS 4.1 was used to examine the measurement and structural models.

The respondents were distributed into male (n=218, 48%) and female (n=228, 52%) groups. The respondents have considerable years of small farming experience, entailing 1-3 years (n=35, 7.8%), 4-6 years (n=121, 27.13%), and 7-9 years (n=123, 27.63%), and over 10 years (n=167, 37.44%). The respondents have experience with mobile apps and devices, as considerable in the study in which AIoT applications could be made accessible for use.

Table 1.
Demographic profile of the respondents.

Attributes	**Frequency (%)**
Gender	
• Male	218 (48%)
• Female	228 (52%)
Education Level	
• High School	138 (31%)
• Bachelor's	246 (55%)
• Master's or Doctorate	62 (14%)
Years of Farming Experience	
• 1 - 3 years	35 (7.8%)
• 4-6 years	121 (27.13%)
• 7-9 years	123 (27.63%)
• 10 and over	167 (37.44%)
Income	
• Below $300 (USD)	64 (14.35%)
• $300 - $600 (USD)	163 (36.55%)
• $600 - $900 (USD)	183 (41.03%)
• Above $900 (USD)	36 (8.07%)

4. Results

4.1. Measurement Model

The study assesses the measurement model by examining the reliability and validity aspects. Cronbach's alpha test was assessed, resulting in a range of 0.6 - 0.9 for the items (acceptable to highly acceptable). Further, composite reliability (CR) resulted in 0.6 - 0.9 for all items. Average variance extracted (AVE) resulted in greater than 0.5 (>0.50). Factor loading confirms that each variable (indicator) investigated is correlated with its associated construct. Results show that the indicators meet the validity requirement, ranging from 0.700 to 0.798. Based on the measurement model results, all constructs fall within the acceptable benchmark values required before proceeding to the analysis of the structural model. Also, the model fit is 0.859.

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Table 2.
Convergent validity.

Construct	Cronbach's Alpha (0.6-0.95)	AVE (>0.50)	CR (rho_c) (0.6-0.95)	Factor Loading (>0.7)	Convergent Validity
PE	0.816	0.556	0.847	0.715 - 0.725	Established
EE	0.807	0.644	0.842	0.701 - 0.733	Established
SI	0.837	0.688	0.857	0.735 - 0.740	Established
FC	0.884	0.699	0.774	0.700 - 0.760	Established
PV	0.811	0.652	0.844	0.702 - 0.748	Established
TR	0.814	0.753	0.846	0.714 - 0.738	Established
GS	0.828	0.775	0.854	0.730 - 0.730	Established
RC	0.819	0.761	0.849	0.721 - 0.798	Established
OC	0.836	0.739	0.854	0.730 - 0.738	Established
IP	0.849	0.707	0.867	0.749 - 0.756	Established
EF	0.840	0.762	0.861	0.701 - 0.733	Established
ENR	0.838	0.720	0.861	0.723 - 0.754	Established

In this study, the heterotrait monotrait ratio (HTMT) was also examined to determine discriminant validity of the constructs. Based on the results, all constructs fall under the acceptable threshold of <0.85, which confirms the discriminant aspect, as presented in Table 2. Similarly, the descriptive results were noted for the constructs such as performance expectancy ($\bar{x} = 5.854$, $\sigma = 0.653$), effort expectancy ($\bar{x} = 5.763$, $\sigma = 0.633$), social influence ($\bar{x} = 5.743$, $\sigma = 0.671$), facilitating conditions ($\bar{x} = 5.451$, $\sigma = 0.673$), government support ($\bar{x} = 5.932$, $\sigma = 0.684$), trust ($\bar{x} = 5.984$, $\sigma = 0.649$) price value ($\bar{x} = 5.362$, $\sigma = 0.6832$), eco-friendly ($\bar{x} = 5.8522$, $\sigma = 0.672$), energy-efficiency ($\bar{x} = 5.77$, $\sigma = 0.681$), resource conservation ($\bar{x} = 5.914$, $\sigma = 0.674$) operating cost saving ($\bar{x} = 5.853$, $\sigma = 5.853$), increased production ($\bar{x} = 5.857$, $\sigma = 0.635$), and intention ($\bar{x} = 6.473$, $\sigma = 0.691$). Overall, the results show moderate to strong agreement.

Table 3.
Heterotrait-monotrait ratio (<0.85).

	$\bar{x}$	σ	OCS	EE	EF	ENR	FC	GS	IP	ITU	PE	PV	RC	SI	TR
OCS	5.853	0.646													
EE	5.763	0.633	0.548												
EF	5.852	0.672	0.605	0.741											
ENR	5.770	0.681	0.532	0.650	0.629										
FC	5.451	0.673	0.501	0.627	0.733	0.638									
GS	5.932	0.684	0.651	0.650	0.618	0.736	0.799								
IP	5.857	0.635	0.633	0.646	0.734	0.616	0.761	0.742							
ITU	6.473	0.691	0.653	0.639	0.739	0.713	0.666	0.728	0.791						
PE	5.854	0.653	0.645	0.628	0.648	0.747	0.743	0.617	0.727	0.727					
PV	5.362	0.6832	0.625	0.745	0.712	0.703	0.633	0.711	0.621	0.649	0.738				
RC	5.914	0.674	0.632	0.653	0.603	0.634	0.701	0.734	0.712	0.721	0.716	0.719			
SI	5.743	0.671	0.629	0.647	0.636	0.731	0.721	0.734	0.716	0.639	0.633	0.728	0.737		
TR	5.984	0.649	0.627	0.626	0.724	0.728	0.717	0.778	0.714	0.732	0.703	0.717	0.706	0.742	

4.2. Structural Model

This study assessed the structural model by examining the r^2, Q^2 and coefficient values. The r^2 is a number between 0 and 1 that measures how well a statistical model predicts an outcome. Based on the results, intention to use ($r^2 = 0.689$) obtained 68.9% of the variance explaining its ability to explain the adoption intention, considering a benchmark of weak (0.25), moderate (0.50), and substantial (0.75). In terms of the predictive accuracy using Q^2 values with benchmarks (higher than 0: small, 0.25: 0.25: medium, 0.50: large), intention to use AIoT results in $Q^2 = 0.521$ value, demonstrating considerable predictive relevance among the endogenous variables. Based on the results, the model was able to establish its predictive relevance on AIoT adoption intention. Lastly, the coefficient values were assessed for all constructs and confirm the relationships, as presented in Table 3.

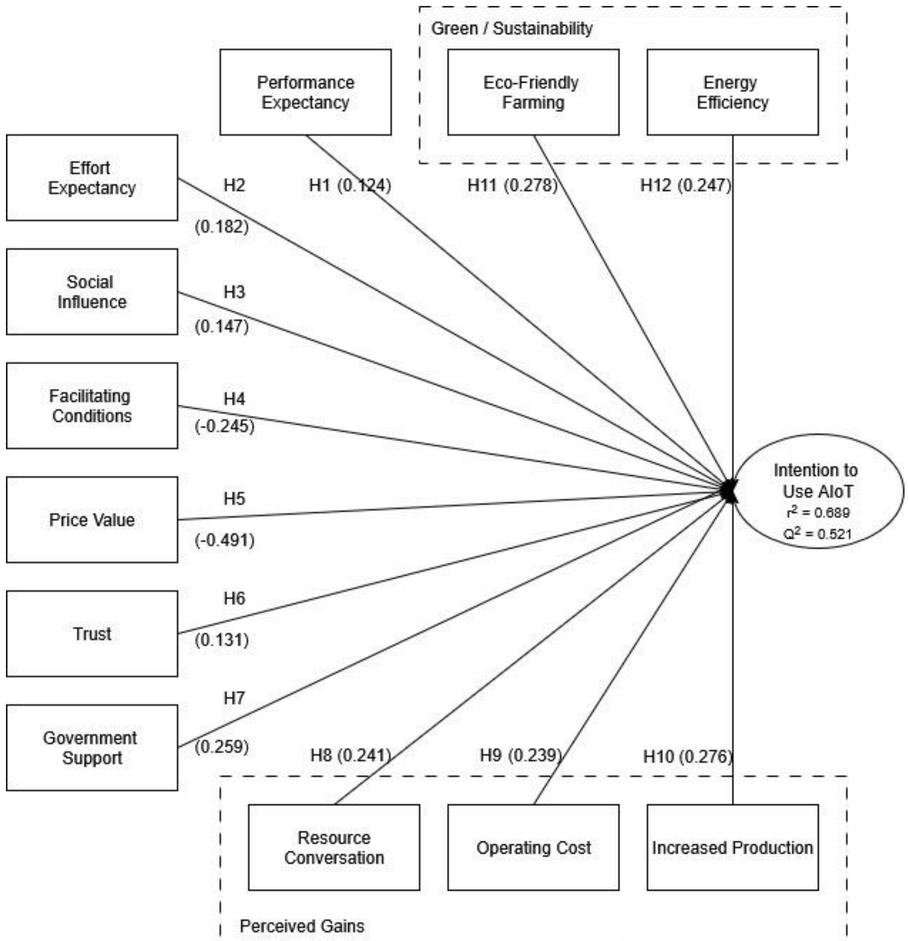

Figure 2.
Structural model on AIoT adoption intention in SFHs.

Table 4.
Hypothesis Testing.

Hypothesis	Path	Coefficient (β)	t-value	p-value	Result
H1	PE → ITU	0.124	2.501	0.012	Supported
H2	EE → ITU	0.182	2.415	0.000	Supported
H3	SI → ITU	0.147	2.085	0.037	Supported
H4	FC → ITU	-0.245	1.431	0.153	Not Supported
H5	PV → ITU	-0.491	0.894	0.210	Not Supported
H6	TR → ITU	0.131	1.753	0.023	Supported
H7	GS → ITU	0.259	3.501	0.000	Supported
H8	RC → ITU	0.241	3.613	0.000	Supported
H9	OC → ITU	0.239	3.642	0.000	Supported
H10	IP → ITU	0.276	2.864	0.000	Supported
H11	EF → ITU	0.278	3.517	0.000	Supported
H12	ENR → ITU	0.247	2.623	0.009	Supported

Note: Significant at p-value < 0.05.

This study confirms that performance expectancy has a significant positive relationship with intention to use ($p = 0.124$, $\beta = 0.012$). Thus, H1 is supported. Similarly, the effort expectancy is positively influential to intention ($p = 0.182$, $\beta = 0.000$). Thus, H2 is supported. While social influence is significantly impacting adoption intention ($p = 0.147$, $\beta = 0.037$). Hence, H3 is supported. Further, this study confirms the negative impact of facilitating conditions with intention to use ($p = 0.153$, $\beta = -0.245$). Therefore, H4 is not supported. With regard to price value with adoption intention ($p = 0.210$, $\beta = -0.491$), this study found a negative impact. Hence, H5 is not supported. The results show that trust of AIoT with existing setup has a significant positive relationship with adoption intention ($p = 0.023$, $\beta = 0.131$). Hence, H6 is supported. With regard to government support, results show that it significantly affects the intention to use AIoT of SFHs ($p = 0.000$, $\beta = 0.131$). H7 is supported.

In relation to sustainability-related factors, this study found that resource conservation has a significant positive impact on intention to use AIoT ($p = 0.000$, $\beta = 0.241$). Thus, H8 is supported. Similarly, operating cost saving as a factor shows a significant positive relationship with intention on AIoT ($p = 0.000$, $\beta = 0.239$) for smart agriculture, thus H9 is supported. Likewise, results show that increased production has a significant effect on intention to use AIoT ($p = 0.000$, $\beta = 0.276$). H10 is supported. When it comes to climate change-related factors, this study found that eco-friendly as a factor has a significant positive impact on intention to use ($p = 0.000$, $\beta = 0.278$). Thus, H11 is supported. While energy-efficiency construct is significant to adoption intention ($p = 0.000$, $\beta = 0.247$). Thus, H12 is supported. Similarly, the energy-efficiency dimension positively affects intention to adopt AIoT.

5. Discussion

The results on performance expectancy are similar with prior studies, confirming its impact on adoption intention [65, 66]. This result indicates that SFHs consider significant importance on the aspect of usefulness and efficiency enhancements in adopting emerging technologies. Similarly, in the study of Miah, et al. [23] and Ena and Siewa [34], effort expectancy is found positively correlated with intention to use and use behavior, which indicates that effort expectancy can reduce perceived complexity and increase acceptance, among SFHs. While this study provides additional evidence that social influence significantly affects intention to use, similar to prior research, which indicates that social influence plays a crucial role to drive technology adoption decisions for SFHs. Also, facilitating conditions are incomparable with the study of Anubhav, et al. [32], which indicates that infrastructure, connectivity, data, and mobile apps can contribute to SFHs' decision to adopt AIoT. While price value is found insignificant, this result is inconsistent with prior work of Bahari, et al. [38], which indicates that value that can be derived from AIoT investment is imperative to pursue it for smart agriculture. In terms of trust factor, the present study is closely similar with prior studies [67, 68], which indicates that SFHs perceive trust as critical to the adoption and sustained use of AIoT technologies for agriculture. Similarly, government support is a crucial element of emerging technologies in agricultural countries, which indicates that SFHs have considerable positive attention to government support to pursue AIoT for smart agriculture.

In terms of the perceived gains, this study confirms resource conservation as essential to SFH intention to use, which indicates that SFHs' focus on efficient utilization of resources can lead to positive economic and environmental gains. Similarly, this study confirms that operating costs that SFHs expected returns on AIoT's for smart agriculture, which indicates it could lead to sustainable agriculture operations. Also, the result on increased production is similar to prior work of Piancharoenwong and Badir [69], which indicates that the SFHs positively perceive that AIoT can lead to anticipated crop yield production gains. Also, the results show that AIoT can be seen as advantageous in attaining eco-friendly agriculture and farming practices, which indicates that it can contribute to greening and sustainable agriculture. Besides, the ability of AIoT to introduce energy efficiency for agriculture is projected to bring balance to farm operations and environmental benefits.

This study contributes to theory by providing evidence of perceived gains (resource conservation, cost savings, increased production), and sustainability factors (eco-friendly, energy-efficient), to understand adoption intention of AIoT from a developing country, the Philippines. Second, AIoT is not yet in full diffusion and implementation in the Philippines due to facilitating factors such as the internet and data, and prices to set up AIoT. Third, this research provides evidence of factors influential to its future adoption. Moreso, the result of this work confirms the role of government support and trust, which were underexplored in past studies of AIoT adoption intention, among small farm holders, both in developed and developing countries.

In practice, this study contributes by providing guidance to the development of policies to further enable the diffusion of AIoT in the Philippines, as a developing country. Small farm holders need government support for awareness and capability building to develop an understanding of its benefits and limitations. Moreso, the government can provide measures to institutionalize programs that enable technology-driven farming such as AIoT while climate change affects SFMs' productivity. Further, the results could provide foundational support to aid small farm holders with necessary tools and technologies to enhance agricultural productivity, resource management, and promote sustainable farming practices. In this way, small farm holders can be assisted in how to scale AIoT in the Philippines and adapt to other emerging economies with similar socio-economic and environmental issues.

6. Conclusion

In this study, adoption intention of AIoT among small farm holders in a developing country is highlighted. A survey was deployed, and partial least squares and structural equation modeling are used to analyze the factors in the conceptual framework. Based on the results, performance expectancy, effort expectancy, social influence, trust, and government support factors were significant in the adoption intention of AIoT, while facilitating conditions and price value did not impact intention to use AIoT for SMFs. Moreso, perceived gain (resource conservation, cost saving, increased production), and sustainability (eco-friendly and energy efficiency) related factors have the most significant impact on intention to use, which indicates the future positive role of AIoT adoption among small farm holders in the Philippines.

This study presents some limitations that future studies may address. Firstly, this study investigated AIoT in a developing country, the Philippines. Thus, the results may not reflect other developing countries and could not be used for generalization. Future studies may consider expanding the contribution of the study and understanding in developing countries. Secondly, this study did not cover issues and challenges faced by small farm holders to pursue AIoT for sustainable and smart agriculture. Lastly, the study did not explore the influence of innovation hubs and institutions as contextual factors in the adoption intention of AIoT. Future research may explore this area to clarify its impact on adoption intention in AIoT.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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