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Exploring Behavioral Drivers Behind Farmers' Willingness to Embrace the Internet of Things

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Abstract

This study explores the factors influencing farmers' willingness to adopt Internet of Things (IoT) technologies in Ghana's agricultural sector, addressing a significant research gap by extending the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) to a demographic and geographical context that has been underexplored in existing literature. A quantitative, non-experimental correlational research design was employed, utilizing Structural Equation Modeling (SEM) to analyze data from 526 participants, including officers from the Ministry of Food and Agriculture and practicing farmers, selected through stratified random sampling. The findings reveal that Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), and Habit (HT) significantly predict Behavioral Intentions (BI) to adopt IoT. Contrary to some previous studies, Price Value (PV) did not emerge as a significant predictor, suggesting a potential need for further investigation in this area. This research is pioneering in applying the UTAUT2 framework to IoT adoption in Ghana's agricultural sector, contributing valuable empirical insights and highlighting new considerations, particularly regarding the roles of Social Influence and Price Value. The study's findings have practical implications for technology developers and agricultural stakeholders, offering guidance on key factors to consider when designing and implementing IoT solutions for farmers. Furthermore, the research has broader social implications, particularly in supporting community outreach and educational programs aimed at enhancing agricultural productivity and improving livelihoods in Ghana through technology adoption.

Keywords: *Internet of Things, Agriculture, Adoption, UTAUT2, Behavioral Intentions*

INTRODUCTION

As a cornerstone of food security and sustainable development, agriculture remains paramount, especially in emerging economies like Ghana. Technological advancements, such as the Internet of Things (IoT), present a transformative avenue to enhance agricultural productivity, a necessity underscored by the pressing global challenge of sustainably feeding a growing population (Bafti, et al., 2023). IoT's applications, ranging from drones and robotics to precision irrigation and livestock monitoring, offer promising advancements for both large-scale and smallholder farmers (Jarial, 2023). However, the integration of IoT in agriculture has not been smooth, largely due to various challenges, both technical and behavioral. While prior studies have shed light on the technological aspects of IoT adoption in agriculture, they have often neglected the human element—specifically, the behavioral factors that influence farmers' willingness to adopt new technologies. Much of the existing research has centered on countries like India, the Middle East, and Bangladesh (Pillai, R. & Sivathanu, 2020; Ronaghi and Forouharfar, 2020; Shi et al., 2022), potentially offering insights that are not wholly transferable to the Ghanaian context.

The current literature, although rich in diverse theoretical frameworks like Behavioral Reasoning Theory (BRT), may not fully encapsulate the psychological intricacies associated with the adoption of IoT in agriculture, particularly in diverse socio-cultural settings (Pillai & Sivathanu, 2020; Jarial, 2023). Moreover, there's a conspicuous absence of research that focuses explicitly on the unique challenges and opportunities within Ghana's agricultural sector, which operates under distinct socio-economic and cultural conditions. It is

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against this backdrop that this study aims to delve into the motivating factors that influence Ghanaian farmers to adopt IoT technologies. Leveraging the Extended Theory of Acceptance and Use of Technology 2 (UTAUT2) as its theoretical framework, the study aspires to fill existing gaps by focusing on the psychological aspects affecting technology adoption in Ghana's agricultural sector. The objective is not merely academic; the research aims to offer actionable insights tailored to the local context, thereby enriching both the theoretical discourse and providing empirical evidence of practical value. This study, therefore, stands as a critical endeavor to understand the behavioral drivers affecting the willingness of Ghanaian farmers to integrate IoT into their farming practices, ultimately contributing to more targeted and effective policy interventions.

LITERATURE REVIEW

Theoretical Review

The study seeks to investigate the behavioral factors that influence farmers in Ghana to adopt Internet of Things (IoT) technologies in agriculture, underpinned by the Extended Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). Developed by Venkatesh et al. (2012), UTAUT2 offers a comprehensive framework for understanding the multifaceted decision-making processes involved in the adoption of new technologies. The theory combines core constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions, which have been adapted and validated across various sectors including Fintech (Chao, 2019; Singh et al., 2021), smart farming (Ronaghi and Forouharfar, 2020), and entrepreneurship (Abushakra and Nikbin, 2019). The model also integrates additional factors like hedonic motivation, price value, and habit, acknowledging that technology adoption is influenced not just by utilitarian motives but also by hedonic and economic considerations. However, existing applications of the UTAUT2 framework reveal several theoretical gaps and inconsistencies. One such gap involves the moderating role of age in technology adoption. While Nordhoff et al. (2020) found a minor negative effect of age, Munyoka and Maharaj (2017) noted a significant positive impact, and Nikolopoulou et al. (2020) found no statistical difference between age groups. These mixed results highlight the need for further empirical validation, especially in contexts like Ghana's agricultural sector, which has its unique challenges and opportunities. Similarly, much of the existing literature has focused on other sectors such as Fintech in banking (Agbetunde et al., 2022; Amoh et al., 2023) and smart farming in the Middle East (Ronaghi and Forouharfar, 2020), leaving a research gap in the application of IoT in agriculture, particularly in developing countries like Ghana. The strength of the UTAUT2 framework lies in its comprehensiveness and flexibility. It integrates various other theoretical models like the Theory of Reasoned Action, Theory of Planned Behaviour, and Technology Acceptance Model, offering a more nuanced understanding of technology adoption behavior (Venkatesh et al., 2012). Its broad applicability across sectors and contexts, as demonstrated in studies ranging from digital wellness services (Mezei et al., 2022) to mobile banking (Farzin et al., 2021), attests to its robustness as a theoretical lens. Moreover, UTAUT2 allows for the incorporation of context-specific factors, making it particularly well-suited for exploring the adoption of IoT in Ghana's unique socio-economic and cultural landscape. Figure 1 illustrates the conceptual framework adapted from Venkatesh et al., (2012)

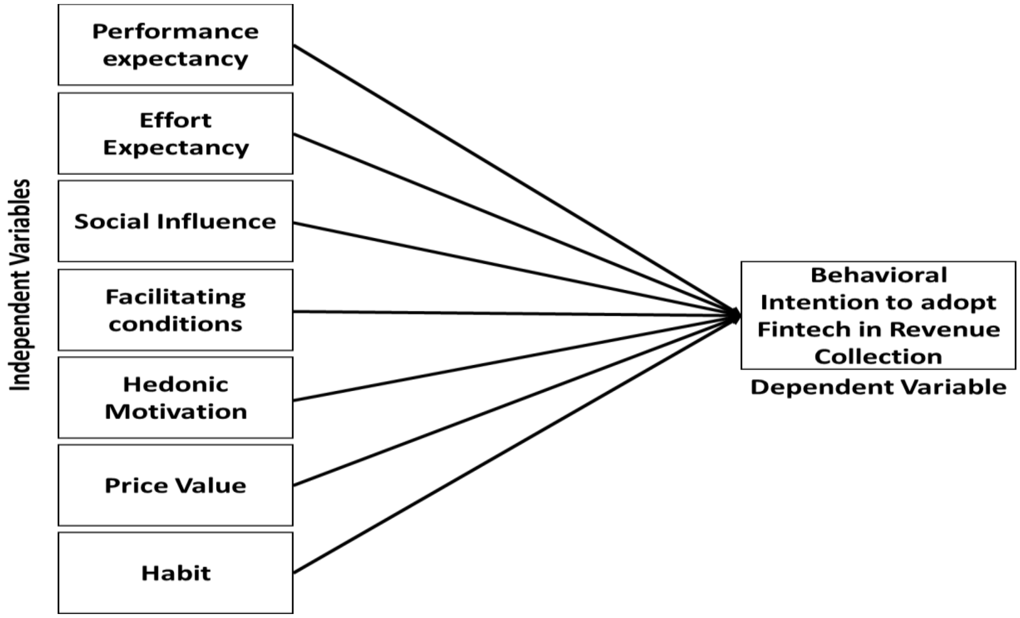

Figure 1: Conceptual Framework

Source: Authors Construct (2023) adapted and modified from Venkatesh et al. (2012)

EMPIRICAL REVIEW

The burgeoning influence of the Internet of Things (IoT) in agriculture has captured the attention of academia, especially in emerging economies. However, the literature reveals gaps and inconsistencies that particularly affect the applicability of these studies in the Ghanaian context. Pillai and Sivathanu (2020) present a seminal work on the adoption of IoT in agriculture in India. The study is methodologically robust, employing Behavioral Reasoning Theory (BRT) and Structural Equation Modeling (SEM) to understand the 'for' and 'against' reasons affecting IoT adoption. Strengths include its pioneering nature and depth of analysis. However, its geographical focus on India limits its applicability to the diverse socio-economic conditions in countries like Ghana. Jarial (2023) extends the discourse to the implications of IoT on Extension Advisory Services (EAS) in India. The paper is academically commendable for delving into the under-researched area of how technology affects human roles in agricultural services. However, its application is limited by its regional focus on India and does not account for places like Ghana, where human intermediaries in agriculture are still indispensable. Arora et al. (2022) offer an analytical lens on the application of Industry 4.0 technologies, including IoT, in the agricultural supply chain. Their multi-method approach, combining DEA and AHP, contributes to its academic rigor. However, the research falls short in considering resource constraints that are more relevant in developing economies like Ghana, narrowing the breadth of its application. Reis et al. (2022) explore a niche but critical aspect of IoT by evaluating a business model focused on the Internet of Services (IoS) in the direct sale of free-range eggs. The study is original and practical, but its single-case study methodology limits its generalizability. While it focuses on the agriculture field, the lack of geographical diversity makes it less applicable to contexts like Ghana. Vasan and Yoganandan (2023) take a unique approach by investigating how cultural beliefs influence the adoption of smart farming technologies. This study is pioneering in linking cultural beliefs with technology adoption, a topic often overlooked. However, its focus on Indian farmers' belief systems restricts its application to other cultural contexts, including Ghana, where different sets of beliefs might exist. Notably, Antwi-Boampong et al. (2022) delve into technology adoption in the Ghanaian context but within the Fintech sector. The study is valuable for highlighting behavioral drivers like performance expectancy and social influence in a Ghanaian context, but its insights have not been extrapolated to the agricultural sector, representing a significant gap.

HYPOTHESIS FORMULATION

PE and Adoption of IoT

The Unified Theory of Acceptance and Use of Technology (UTAUT) and its extended version UTAUT2 serve as comprehensive frameworks for understanding the factors that influence technology adoption (Venkatesh et al., 2012). Within these frameworks, Performance Expectancy (PE) is highlighted as a significant predictor of Behavioral Intention (BI) to use technology. PE refers to the degree to which an individual believes that using a particular technology will enhance their job performance. In the context of agriculture, if farmers perceive that IoT technologies will improve their agricultural yield or efficiency, they are more likely to intend to use such technologies. Several empirical studies have supported the role of PE in influencing BI in various technological contexts. For example, a study by Abushakra and Nikbin (2019) found that information technology knowledge significantly impacted entrepreneurs' acceptance and adoption of IoT, echoing the importance of performance expectancy. Moreover, research by Shi et al. (2022) confirmed that performance expectancy, among other factors, influenced the willingness of Bangladeshi farmers to adopt IoT in agriculture. This study also used Structural Equation Modeling (SEM), the same methodological approach proposed for the present study. In another empirical investigation in the context of Iran, Ronaghi and Forouharfar (2020) utilized the UTAUT model to highlight the positive impacts of performance expectancy on the intention to use IoT technology in smart farming. While these studies offer valuable insights into IoT adoption in different geographical and sectoral contexts, none have focused on the specific case of farmers in Ghana. Therefore, the proposed research aims to fill this gap by investigating how performance expectancy affects Ghanaian farmers' behavioral intentions towards adopting IoT technologies. Given the theoretical framework of UTAUT and the empirical evidence suggesting the influence of PE on BI, the following hypothesis is formulated for the context of IoT adoption in agriculture among farmers in Ghana:

Ha_1: There is a positive relationship between Performance Expectancy (PE) and Behavioral Intention (BI) to adopt IoT technologies among farmers in Ghana.

PE and Adoption of IoT

The concept of Effort Expectancy (EE) is a critical component within the Unified Theory of Acceptance and Use of Technology (UTAUT) and its extension, UTAUT2 (Venkatesh et al., 2012). EE reflects the degree of ease associated with the use of technology and has been posited as a significant predictor of Behavioral Intention (BI) to adopt and use technology. In the context of agriculture, Effort Expectancy could influence farmers' willingness to adopt Internet of Things (IoT) technologies, as farmers may be more inclined to use technology that they find easy to use. Several empirical studies have demonstrated the impact of EE on BI. For instance, Tamilmani et al. (2020) and Weeger et al. (2018) found a positive correlation between EE and the adoption of Fintech. A study by Abushakra and Nikbin (2019) on IoT adoption among entrepreneurs also revealed similar findings. Additionally, research on the adoption of IoT in agriculture in Bangladesh by Shi et al. (2022) confirmed that Effort Expectancy significantly influenced farmers' willingness to adopt IoT. Similarly, Ronaghi and Forouharfar (2020) reported that EE played a significant role in the intention of farmers in Iran to adopt IoT technologies. However, these studies are primarily focused on entrepreneurs and farmers in Bangladesh and Iran, leaving a gap in the literature regarding the influence of Effort Expectancy on farmers' BI towards IoT adoption in other settings, such as Ghana. Given the theoretical framework of UTAUT and the empirical evidence supporting the relationship between Effort Expectancy and Behavioral Intention, the following hypothesis is formulated for the context of IoT adoption in agriculture among farmers in Ghana:

Ha_2: There is a positive relationship between Effort Expectancy (EE) and Behavioral Intention (BI) to adopt IoT technologies among farmers in Ghana.

SI and Adoption of IoT

Social Influence (SI) is a key construct in the Unified Theory of Acceptance and Use of Technology (UTAUT) and its extension, UTAUT2 (Venkatesh et al., 2012). SI refers to the degree to which individuals perceive that important others believe they should use a particular technology. In the context of agriculture, the recommendations and endorsements from peers, community leaders, and even agronomic experts could significantly influence a farmer's Behavioral Intention (BI) to adopt Internet of Things (IoT) technologies for farming practices. Empirical studies have consistently shown the impact of SI on BI. For instance, Tamilmani et al. (2021) and Weeger et al. (2018) reported a positive correlation between SI and the adoption of technology. Specifically, in the agriculture sector, Ronaghi and Forouharfar (2020) found that SI was a significant predictor of farmers' intention to use IoT technology in Iran. However, there are cases where the impact of SI is not clear-cut. For example, a study by Boison et al. (2023) found that SI and BI were not related, suggesting that the influence of SI may depend on specific contextual factors. Considering both the theoretical framework and empirical evidence, the hypothesis for the study can be formulated as follows:

Ha_3: There is a positive relationship between Social Influence (SI) and Behavioral Intention (BI) to adopt IoT technologies among farmers.

FC and Adoption of IoT

Facilitating Conditions (FC) is one of the key constructs in the Unified Theory of Acceptance and Use of Technology (UTAUT) and its extended model UTAUT2. It refers to the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of a system (Venkatesh et al., 2012). In the context of agriculture and IoT adoption, facilitating conditions can include access to necessary hardware and software, technical support, training programs, and favorable policy environments. Empirical studies have generally found a positive relationship between FC and BI. A study on Bangladeshi farmers by Shi et al. (2022) indicated that facilitating conditions are one of the factors influencing farmers' willingness to adopt IoT. Similarly, a study on IoT adoption in Iran showed that facilitating conditions had a positive impact on behavioral intention to use IoT technology in agriculture (Ronaghi and Forouharfar, 2020). In the context of Fintech, facilitating conditions have been found to be positively correlated with behavioral intention to adopt financial technology services, as indicated by studies like those of Dwivedi et al. (2017) and Ouattara (2017). Based on the theoretical and empirical foundations, the following hypothesis can be formulated for the study as follows:

Ha_4: There is a positive relationship between Facilitating Conditions (FC) and Behavioral Intention (BI) to adopt IoT technologies among farmers.

HM and Adoption of IoT

Hedonic Motivation (HM) refers to the intrinsic enjoyment or pleasure that individuals experience when using a particular technology. According to the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), HM is one of the critical factors influencing behavioral intention to adopt a technology (Venkatesh et al., 2012). In the context of agriculture and IoT, HM could manifest as the perceived enjoyment farmers get from using IoT technologies, which could simplify their tasks or bring them closer to the state-of-the-art in farming techniques. Empirical research supports the role of HM in technology adoption. The study by Shi et al. (2022) in the context of Bangladeshi farmers did mention hedonic motivation as one of the factors influencing the willingness to adopt IoT. Moon and Tamilmani et al. (2020) and Soodan et al. (2020) also found a positive link between HM and Fintech adoption. Similarly, Ouattara (2017) identified HM as a significant predictor of employees' behavioral intention to adopt technology. These studies lend empirical support to the theoretical construct of HM in the context of technology adoption. Based on these theoretical and empirical foundations, the following hypothesis can be formulated for the study as follows:

Ha_5: There is a positive relationship between Hedonic Motivation (HM) and Behavioral Intention (BI) to adopt IoT technologies among farmers.

PV and Adoption of IoT

Price Value (PV) refers to the perceived utility gained from using a technology relative to its cost. In the context of IoT in agriculture, this could mean the perceived benefits farmers expect to derive from IoT technologies in relation to what they cost. The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) suggests that price value is a significant predictor of technology adoption (Venkatesh et al., 2012). This implies that if farmers perceive the value gained from using IoT technologies as outweighing their costs, they are more likely to adopt them. Empirical research also supports the importance of PV in technology adoption. The study by Shi et al. (2022) found that price value is one of the factors influencing the willingness of Bangladeshi farmers to adopt and pay for IoT in agriculture. Studies in the fintech sector, such as those by Blut et al. (2022) and Ouattara (2017), have also found a positive correlation between price value and technology adoption. These studies indicate that individuals, when they perceive higher value relative to cost, are more likely to intend to adopt a technology, providing empirical grounding for the theoretical construct. Based on the theoretical and empirical foundations, the following hypothesis can be formulated as follows:

Ha_6: There is a positive relationship between Price Value (PV) and Behavioral Intention (BI) to adopt IoT technologies among farmers.

HT and Adoption of IoT

Habit (HT) is defined as the extent to which individuals engage in a behavior automatically, usually due to learning that has occurred through repeated past performance (Venkatesh et al., 2012). In the context of IoT in agriculture, the habit would refer to the degree to which farmers have developed automatic behaviors or routines in using IoT technologies for farming activities. According to the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), habit is an essential predictor of technology adoption (Venkatesh et al., 2012). If farmers have developed a habit of using IoT technologies due to the perceived benefits or ease of use, they are more likely to continue adopting these technologies. Several empirical studies support the influence of habit on technology adoption. While the study by Shi et al. (2022) did not specifically focus on habit, it did consider several behavioral factors, including hedonic motivation and facilitating conditions that could contribute to habit formation. In the fintech sector, Puspitaningsih et al. (2023), Yang et al. (2020), and Zhang et al. (2021) found a positive relationship between habit and the intention to adopt fintech technologies. These studies indicate that when individuals develop a habit of using a technology, they are more likely to continue using it, providing an empirical basis for the influence of habit on IoT adoption in agriculture. Given the theoretical and empirical foundations, the following hypothesis can be formulated for the study as follows:

Ha_7: There is a positive relationship between Habit (HT) and Behavioral Intention (BI) to adopt IoT technologies among farmers.

METHODOLOGY

The study adopted a quantitative non-experimental correlational research design, aligned with the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework (Venkatesh et al., 2012). This design was considered suitable for addressing research questions focused on identifying relationships between multiple variables and understanding cause-and-effect connections (Creswell, 2014; Vogt, 2012). The approach allowed for the empirical testing of hypotheses regarding farmers' behavioral intentions to adopt IoT technologies. The focus of the study was on the agricultural sector, and a sample of 526 participants was selected, comprising both officers from the Ministry of Food and Agriculture and practicing farmers. Stratified random sampling was utilized, with strata based on regions and types of farms. The sample was proportionally distributed across these strata (Zhang, Tan & Hu, 2020). A power analysis was conducted to ensure that the sample size was both sufficient and efficient for the study, thereby enhancing the validity of the results (Wen et al., 2018; Fowler & Lapp, 2019). Data were collected using a structured questionnaire, administered through an online survey tool to ensure a wide reach. The questionnaire was divided into three main sections: demographic information, factors influencing the adoption of IoT, and the current level of IoT technology adoption among farmers. The factors investigated included performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, and behavioral intentions (Raza et al., 2019). To maintain ethical standards, ethical clearance was obtained from the Institutional Review Board (IRB) of the researcher's institution. Informed consent was secured from all participants, ensuring voluntariness, justice, and fairness in the process. Data were collected over a 30-day period, and stringent measures were taken to guarantee participants' confidentiality and anonymity, adhering to data protection protocols such as encryption and password protection. For data analysis, the raw data were downloaded, encrypted, and stored securely while being deleted from the online survey platform. The analysis involved multiple steps including data preparation, descriptive statistics, assumption testing, and hypothesis testing. Structural Equation Modeling (SEM) was employed as the statistical tool for the analysis, allowing for the examination of complex relationships between the variables (Kumar & Gupta, 2021). Several tests were conducted to ensure the validity and reliability of the data, such as discriminant validity, and reliability analysis (Hair et al., 2014).

RESULTS

Demographic Features of Respondents

The demographic features of the respondents, as presented in Table 1, indicate a noteworthy gender imbalance among the participants of the study. Specifically, a majority of the respondents were female, accounting for 62.5% of the total sample, compared to the 37.5% who were male. This disproportionality in gender distribution raises questions about whether the views of male participants are adequately represented in the study. The gender imbalance may also have implications for the generalizability of the study findings. However, if the agricultural sector in the study area is predominantly female-driven, this distribution could be reflective of the target population. Therefore, the gender imbalance may or may not be a limitation, depending on the specific context of the agricultural sector being studied.

The age distribution of the respondents reveals interesting patterns. A minimal number of respondents fell into the 15-24 age group, making up only 5.1% of the sample. In contrast, the majority of respondents were concentrated in the 35-44 age bracket, representing 33.5% of the sample. This was closely followed by the 45-54 age group, accounting for 27.0%. These figures suggest that the study predominantly captures the perspectives of middle-aged individuals, who are presumably more experienced and established in the agricultural sector. The 25-34 age group also had significant representation at 24.0%. However, older age groups, specifically those aged 55 and above, were underrepresented, making up just 10.5% of the sample.

The data indicate a concentration of respondents in the mid to late working-age range, with a lean toward female representation. This could be justified if the aim of the study was to capture the perspectives of more experienced and possibly more stable participants in the agricultural sector. However, the underrepresentation of younger and older age groups, as well as the gender imbalance, may limit the study's ability to fully capture the diverse range of experiences and perspectives in the agricultural sector. Thus, while the data provides valuable insights, these demographic skews should be acknowledged as potential limitations when interpreting the study's findings.

Table 1: Demographic Features of respondents

Measure	Group	Frequency	Percentage
Gender	Male	197	37.5%
	Female	329	62.5%
Age	15-24	27	5.1%
	25-34	126	24.0%
	35-44	176	33.5%
	45-54	142	27.0%
	55-64	43	8.2%
	64 and above	12	2.3%

Source: Survey Data (2023)

The Measurement Model

The measurement model analysis table provides key insights into the reliability and validity of the constructs used in the study. In terms of reliability, the Cronbach's Alpha and Composite Reliability (CR) provide useful metrics. A commonly accepted threshold for Cronbach's Alpha is 0.7 or above for research purposes (Tavakol & Dennick, 2011). Most constructs, such as Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), Habit (HT), and Behavioral Intentions (BI), met this threshold, confirming their internal consistency. However, the Social Influence (SI) and Price Value (PV) constructs had alarmingly low Cronbach's Alpha scores, suggesting poor reliability for these constructs (Hair et al., 2010). Similarly, CR values for most constructs are above 0.7, indicating good reliability (Fornell & Larcker, 1981). However, Social Influence (SI) and Price Value (PV) fall short, further highlighting their questionable reliability. Factor loadings offer an initial validation of the constructs. A loading of 0.7 or above is generally considered satisfactory (Hair et al., 2010). Most items across the constructs meet this criterion, except for some in Social Influence and Price Value, which corroborates their lower reliability scores.

Average Variance Extracted (AVE) measures the amount of variance captured by the construct in relation to the variance due to measurement error, and values should be 0.5 or higher for a good fit (Fornell & Larcker, 1981). Except for Social Influence (SI) and Price Value (PV), all constructs exceed this threshold, indicating a satisfactory level of convergent validity. The study's measurement model mostly shows good reliability and validity, but there are concerns about the Social Influence and Price Value constructs. The poor reliability and validity metrics for these two constructs suggest that they may not be suitable for further analyses or for drawing credible conclusions, and thus may require a reevaluation of the items or a different measurement approach. The high reliability and validity of constructs like Facilitating Conditions (FC), Habit (HT), and Behavioral Intentions (BI) add robustness to these constructs, making them reliable for further structural model analyses. Their high AVE values also support the discriminant validity, ensuring that these constructs are distinctly different from each other (Hair et al., 2014).

Table 2: Results for the Measurement Model Analysis

UTAUT	N of Items	Items	Factor Loading	Cronbach's Alpha	CR	AVE
Performance expectancy (PE)	5	PE1	0.738	0.861	0.900	0.644
		PE2	0.757			
		PE3	0.776			
		PE4	0.865			
		PE5	0.865			
Effort expectancy (EE)	5	EE1	0.897	0.873	0.905	0.664
		EE2	0.920			
		EE3	0.765			
		EE4	0.895			
		EE5	*0.532*			
Social Influence (SI)	***4***	***SI1***	***0.737***	***0.013***	***0.768***	***0.455***
		SI2	*0.561*			
		SI3	*0.656*			
		SI4	0.730			
Facilitating Conditions (FC)	3	FC2	0.933	0.932	0.957	0.881
		FC3	0.947			
		FC4	0.937			
Hedonic Motivation (HM)	2	HM1	0.962	0.923	0.962	0.926
		HM2	0.962			
Price Value (PV)	***4***	***PV1***	***0.753***	***0.147***	***0.796***	***0.497***

		PV2	*0.657*			
		PV3	*0.600*			
		PV4	0.792			
Habit (HT)	4	HT1	0.901	0.921	0.944	0.808
		HT2	0.885			
		HT3	0.898			
		HT4	0.911			
Behavioral Intentions (BI)	5	BI1	0.964	0.954	0.965	0.846
		BI2	0.928			
		BI3	0.964			
		BI4	0.793			
		BI5	0.939			

Source: Survey Data (2023)

Discriminant Validity

The discriminant validity of the research instrument was assessed using the Fornell-Larcker criterion, as proposed by Fornell and Larcker in 1981. This criterion compares the square roots of the Average Variance Extracted (AVE) to the correlation coefficients between constructs to establish the validity of the constructs in differentiating the variables under study. Table 3 indicates the results of the discriminant validity analysis. According to the Fornell-Larcker criterion, a construct has adequate discriminant validity if the square root of its AVE is greater than its correlation with any other construct in the model (Fornell & Larcker, 1981). In our data, the diagonal values (representing the square roots of AVEs for each construct) are greater than the off-diagonal values in their corresponding rows and columns (correlations between constructs). For instance, the square root of AVE for Performance Expectancy (PE) is 0.802, and this value is greater than any other correlation involving PE, thereby fulfilling the condition for discriminant validity.

Similarly, EE shows a square root of AVE value of 0.815, which is greater than its highest correlation with any other construct (0.703 with Behavioral Intentions - BI). This pattern holds for all the constructs, including Social Influence (SIL), Facilitating Conditions (FC), Hedonic Motivation (HM), Price Value (PV), Habit (HT), and Behavioral Intentions (BI). Thus, the constructs meet the conditions for discriminant validity as specified by the Fornell-Larcker criterion. This implies that the constructs are well-differentiated and measure distinct phenomena, thereby validating the utility of the instrument for this specific research context (Fornell & Larcker, 1981).

Table 3: Results for Discriminant Validity Analysis

	PE	EE	SIL	FC	HM	PV	HT	BI
PE	**0.802**							
EE	0.540	**0.815**						
SIL	0.111	0.281	**0.675**					
FC	0.392	0.615	0.155	**0.777**				
HM	0.377	0.668	0.133	0.682	**0.857**			
PV	*0.167*	*0.239*	*0.088*	*0.387*	*0.267*	***0.247***		
HT	*0.370*	*0.685*	*0.200*	*0.710*	*0.790*	*0.257*	***0.653***	
BI	*0.360*	*0.703*	*0.207*	*0.672*	*0.708*	*0.250*	*0.815*	***0.716***

Source: Survey Data (2023)

Hypotheses Testing

Firstly, Performance Expectancy (PE) had a significant positive impact on Behavioral Intentions (BI) with a coefficient (β) of 1.100. The p-value of 0.000 and z-value of 8.660 indicate strong statistical significance, supporting the hypothesis that farmers are likely to adopt IoT if they perceive it will improve their performance. Similarly, Effort Expectancy (EE) exhibited a significant positive impact on BI, with a coefficient of 0.953 and a p-value of 0.000. The z-value of 21.110 reinforces this result, indicating that the ease of use of IoT technology is a major factor affecting farmers' adoption intentions. Social Influence (SI) also showed a positive impact on BI, but with a higher coefficient of 3.591. However, the standard error is relatively high at 1.736. Despite this, the p-value of 0.039 confirms that SI is significant at the alpha level of 0.05. Facilitating Conditions (FC) had a coefficient of 0.828 and a p-value of 0.000, signifying a strong positive relationship with BI. The high z-value of 18.460 further supports this relationship, indicating that external conditions that make it easier to use IoT are significant for its adoption. Hedonic Motivation (HM) had a strong positive effect on BI, with a coefficient of 0.959 and a p-value of 0.000. This suggests that enjoyment derived from using IoT is a crucial factor in influencing farmers' willingness to adopt the technology. Interestingly, Price Value (PV) was found to be not significant, with a negative coefficient of -0.079 and a high p-value of 0.773. This suggests that the cost of IoT technology may not be a determining factor in its adoption by farmers, contrasting some earlier studies (Venkatesh et al., 2012). Lastly, Habit (HT) showed a significant positive influence on BI, with a coefficient of 1.049 and a p-value of 0.000. This indicates that farmers who have formed a habit of using technologies are more likely to adopt IoT.

Table 4: Hypotheses Test Results based on Structural Model (Alpha=0.05)

Hypothesis	Coef. (β)	Std. Error.	z	P>|z|	Decision
PE=>BI	1.100	0.127	8.660	0.000	Significant
EE=>BI	0.953	0.045	21.110	0.000	Significant
SI=>BI	3.591	1.736	2.070	0.039	Significant
FC=>BI	0.828	0.045	18.460	0.000	Significant
HM=>BI	0.959	0.047	20.340	0.000	Significant
PV=>BI	-0.079	0.272	-0.290	0.773	Not Significant
HT=>	1.049	0.200	5.250	0.000	Significant

Source: Survey Data (2023)

DISCUSSION

The study presented an in-depth investigation into the behavioral drivers affecting farmers' willingness to adopt Internet of Things (IoT) technology in agriculture, utilizing the Unified Theory of Acceptance and Use of Technology (UTAUT) as a guiding framework. Below is a synthesis of the study's findings, framed around the hypotheses.

PE and Adoption of IoT

The study's results offer compelling evidence that Performance Expectancy (PE) significantly influences farmers' Behavioral Intentions (BI) to adopt Internet of Things (IoT) technologies in agriculture. A coefficient (β) of 1.100, combined with a p-value of 0.000 and a z-value of 8.660, underscores the statistical significance of this relationship. These quantitative results provide robust support for the hypothesis that farmers are likely to adopt IoT technologies if they believe that these technologies will improve their performance, such as increasing crop yields, reducing labor costs, or enhancing resource management. This finding is consistent with existing literature. For example, Abushakra and Nikbin (2019) found that entrepreneurs' knowledge of information technology, particularly how it could enhance their business performance, was a significant factor in their adoption of IoT. Similarly, Ronaghi and Forouharfar (2020) utilized the UTAUT model to examine Iranian farmers and found a strong positive impact of performance expectancy on the intention to adopt smart farming technologies. In both these studies, the role of PE as a key determinant of technology adoption was emphatically validated. However, what sets this study apart is its focus on the agricultural sector within the socio-economic and cultural context of Ghana. While previous studies have investigated the role of PE in technology adoption, they have often been situated in different geographic locations or industrial sectors. This study, therefore, contributes to the academic discourse by extending the understanding of PE's role in technology adoption to a specific demographic that has been understudied, namely, Ghanaian farmers. Moreover, the study's findings have practical implications. Given the demonstrated importance of PE in influencing IoT adoption, agricultural policymakers and stakeholders in Ghana could target their interventions more effectively. For instance, educational and training programs could be designed to explicitly demonstrate how IoT technologies can lead to better farming outcomes, thereby enhancing farmers' performance expectancy and, in turn, their willingness to adopt such technologies.

EE and Adoption of IoT

The study revealed that Effort Expectancy (EE) plays a significant role in influencing Behavioral Intentions (BI) to adopt Internet of Things (IoT) technologies among farmers. With a coefficient of 0.953 and a p-value of 0.000, coupled with a z-value of 21.110, the statistical evidence robustly supports the hypothesis that the perceived ease of use of IoT technologies is a major determinant in farmers' willingness to adopt them. In simpler terms, if farmers find IoT technologies straightforward and convenient to use, they are more likely to integrate these technologies into their agricultural practices. This result aligns well with previous empirical research on technology adoption across various sectors. Tamilmani et al. (2020) found a positive correlation between EE and the adoption of Fintech technologies, emphasizing that the perceived ease of using a technology can significantly impact its acceptance. Additionally, Shi et al. (2022) confirmed that Effort Expectancy was a crucial factor influencing Bangladeshi farmers' decisions to adopt IoT technologies. Both studies underscore the universal relevance of EE as a key predictor in the adoption of new technologies. However, the unique contribution of the present study lies in its focus on the agricultural sector within the specific cultural and economic landscape of Ghana. While prior research has indeed highlighted the role of EE in technology adoption, these studies often did not specifically address the unique challenges and opportunities facing farmers, particularly in developing countries like Ghana. Therefore, this study fills an existing gap in the literature by extending the theoretical construct of EE to a less-studied, but highly relevant, demographic. Practically speaking, the study's findings have important implications for both policymakers and agricultural technology developers. Knowing that ease of use is a critical factor in farmers' willingness to adopt IoT, interventions can be tailored to minimize the complexity associated with using these technologies. For instance, user-friendly interfaces, localized language support, and hands-on training sessions could be developed to make IoT technologies more accessible and less intimidating for farmers, thereby enhancing their effort expectancy.

SI and Adoption of IoT

The study's findings revealed that Social Influence (SI) had a notable impact on Behavioral Intentions (BI) for adopting Internet of Things (IoT) technologies among farmers. The coefficient value of 3.591 indicates a relatively strong effect, although the standard error of 1.736 suggests that there may be some variability in this relationship. Nevertheless, with a p-value of 0.039, the study confirms that SI is statistically significant at the alpha level of 0.05, indicating that the impact of social factors on the willingness of farmers to adopt IoT technologies should not be discounted.

The results of this study are consistent with existing literature in some respects. For example, Tamilmani et al. (2021) reported a positive correlation between Social Influence and the adoption of technology. This is indicative of a broader trend where peer pressure, community norms, or recommendations from trusted authorities can strongly influence an individual's intention to adopt new technologies. However, the findings also present a nuanced picture when considered in the context of other research. Boison et al. (2023) found that the relationship between SI and BI was not significant, thereby introducing a layer of complexity to the role of SI in technology adoption. This discrepancy may be attributable to various contextual factors such as cultural norms, social structures, or even the type of technology being considered. What sets this study apart is its application to the specific context of agriculture in Ghana. While Social Influence has been studied in other sectors and geographies, the unique socio-cultural dynamics of Ghana present a different set of influencers and community structures that can affect technology adoption. For example, in communities where traditional agricultural methods are deeply rooted, the influence of community leaders or elder farmers can be pivotal in swaying opinions either for or against the adoption of new technologies like IoT. From a practical standpoint, understanding the role of Social Influence in the adoption of IoT technologies can guide targeted interventions. For example, awareness campaigns or educational programs could be designed to leverage social networks and influential community members to positively influence farmers' perceptions of IoT technologies. Alternatively, partnerships could be formed with respected local organizations or individuals to endorse the adoption of IoT, thus increasing its social acceptability and desirability among farmers.

FC and Adoption of IoT

The study demonstrated that Facilitating Conditions (FC) significantly influence Behavioral Intentions (BI) to adopt Internet of Things (IoT) technologies in agriculture. The coefficient of 0.828, coupled with a p-value of 0.000, strongly supports this relationship, confirming the hypothesis that an enabling environment is essential for farmers to adopt IoT. The high z-value of 18.460 further solidifies the robustness of these findings. This outcome aligns well with existing literature. For example, Shi et al. (2022) identified facilitating conditions as one of the key factors affecting farmers' willingness to adopt IoT technologies in Bangladesh. In the broader context of technology adoption, Dwivedi et al. (2017) found facilitating conditions to be positively correlated with behavioral intentions to adopt financial technology services. The current study adds depth to these findings by extending them to the particular setting of agriculture in Ghana, a context that has been less represented in existing literature. The significance of Facilitating Conditions in this study cannot be overstated, especially in the context of emerging economies like Ghana, where infrastructural and institutional supports can be lacking. Facilitating Conditions in the agricultural sector can encompass a wide range of factors, such as availability and accessibility of technical support, quality of internet connectivity, and ease of access to necessary hardware and software. Additionally, an enabling policy environment that encourages investment in agricultural technology can also be considered a facilitating condition. From a practical standpoint, the study's findings are invaluable for policymakers and stakeholders in the agricultural sector. The strong influence of Facilitating Conditions on Behavioral Intentions suggests that investments in infrastructure, training, and policy reform could significantly enhance the rate of IoT adoption among farmers. For instance, the government and other stakeholders could consider initiatives such as subsidized rates for internet connectivity in rural areas, farmer training programs on IoT technologies, and policy incentives for tech companies to develop farmer-friendly IoT solutions.

Moreover, the study offers valuable insights for future research. Given that facilitating conditions have been shown to be crucial in technology adoption across different sectors and countries, further research could explore the specific types of facilitating conditions that are most impactful in the agricultural context, as well as how these may vary across different farming practices and scales of operation.

HM and Adoption of IoT

The current study revealed that Hedonic Motivation (HM) has a significant positive impact on Behavioral Intentions (BI) to adopt Internet of Things (IoT) technologies in agriculture. The coefficient of 0.959 and a p-value of 0.000 robustly confirm this relationship. The findings are in line with existing research, such as studies by Moon and Tamilmani et al. (2020) and Soodan et al. (2020), which also found a positive correlation between HM and technology adoption. However, the current study goes beyond previous research by emphasizing the role of HM specifically in the agricultural sector and within the Ghanaian context, which has not been adequately explored in the existing literature. Hedonic Motivation refers to the intrinsic enjoyment or satisfaction gained from engaging in an activity. In the context of IoT adoption in agriculture, this could mean the pleasure farmers derive from using advanced technologies that make their work more efficient or engaging. The significance of HM in this study contradicts the commonly held belief that utilitarian factors like performance expectancy or effort expectancy are the primary drivers of technology adoption in professional settings such as agriculture. The substantial role of Hedonic Motivation in influencing BI to adopt IoT technologies has practical implications for developers and marketers of agricultural technologies. Understanding that farmers value the 'enjoyment factor' could guide the design and marketing strategies for

IoT solutions targeted at this demographic. For instance, incorporating user-friendly interfaces, gamification elements, or aesthetically pleasing designs could enhance the user experience, thereby boosting the hedonic motivation to adopt these technologies. From a policy perspective, the importance of hedonic factors should not be underestimated. Programs designed to promote technology adoption in agriculture often focus on practical benefits like increased yields or labor-saving features. While these are undoubtedly crucial, adding elements that make the technology enjoyable to use could significantly improve adoption rates. This could involve anything from holding interactive workshops that allow farmers to 'play' with new technologies to developing community initiatives that make the adoption of new technologies a more socially engaging experience.

PV and Adoption of IoT

The study yielded intriguing results regarding the role of Price Value (PV) in influencing Behavioral Intentions (BI) to adopt Internet of Things (IoT) technologies in agriculture. Unlike most other variables in the Unified Theory of Acceptance and Use of Technology (UTAUT) model, Price Value did not emerge as a significant predictor, with a coefficient of -0.079 and a high p-value of 0.773. These findings are in stark contrast to existing research such as the study by Blut et al. (2022), which found a positive correlation between Price Value and technology adoption. Price Value typically refers to the perceived utility or benefits gained from using a technology relative to its cost. The absence of its significance in this study is particularly noteworthy because it suggests that, for the farmers surveyed, the economic or financial aspects of IoT technologies may not be the primary consideration in their adoption decision-making. This is somewhat counterintuitive given that farming, particularly in developing economies like Ghana, is often constrained by budget limitations. This result could be interpreted in a few ways. One possibility is that farmers perceive the benefits of IoT technologies to be so substantial that they outweigh concerns about cost. Alternatively, it could mean that farmers have access to subsidies, grants, or other financial support mechanisms that mitigate the impact of cost. It is also possible that the sample of farmers surveyed already had a reasonably high level of financial stability, making cost a less significant factor in their decision-making process. From a policy perspective, this finding could have important implications. If cost is not a significant barrier to IoT adoption among farmers, then policy initiatives might better focus on other areas such as improving facilitating conditions or enhancing effort expectancy. However, it's crucial to note that these findings are specific to the surveyed population and may not be generalizable. Therefore, policymakers should conduct further research to validate these results in broader contexts. For technology providers, the non-significance of Price Value suggests that marketing strategies might be more effective if they focus on other value propositions of IoT technologies, such as ease of use (Effort Expectancy) or potential performance gains (Performance Expectancy).

HT and Adoption of IoT

The study found that Habit (HT) plays a vital role in influencing Behavioral Intentions (BI) to adopt Internet of Things (IoT) technologies among farmers. The coefficient for Habit was 1.049, and the p-value was 0.000, affirming its statistical significance. This aligns with prior research in different sectors, notably in fintech, where studies by Puspitaningsih et al. (2023) and Yang et al. (2020) have also highlighted the impact of Habit on technology adoption. Habit is defined in the Unified Theory of Acceptance and Use of Technology (UTAUT) model as the extent to which individuals engage in a behavior automatically, usually due to learning that has occurred through repeated past performance. In the context of agriculture and IoT, this could refer to farmers who have already integrated technology into some aspects of their farming practices. These farmers would find it easier to adopt new IoT technologies as they have developed a routine or "habit" around technology use. The significance of Habit in this study underscores the importance of early adoption and consistent usage in technology assimilation processes. Farmers who have already begun integrating basic digital technologies into their work routines are more likely to be open to adopting more advanced technologies like IoT. From a practical standpoint, these findings suggest that strategies aimed at increasing the initial adoption of simpler technologies could pave the way for the more widespread adoption of complex technologies like IoT in the future. For policymakers and stakeholders in agricultural development, the significance of Habit implies that training programs and initial introductions to technology can have a long-lasting impact. Early positive experiences with technology can create a feedback loop, reinforcing continuous adoption and creating a culture of innovation and openness to new technologies. Moreover, for technology developers and providers, understanding the role of Habit in technology adoption can offer insights into how to design IoT solutions for agriculture. User-friendly interfaces and functionalities that align with farmers' existing workflows can contribute to the formation of positive usage habits, thereby fostering sustained adoption over time. However, it's important to note the contextual specificity of these findings. The study was conducted among a particular demographic, and the significant role of Habit in this context may not necessarily be generalizable to other populations or sectors. Additional research could explore the role of Habit in different farming communities and under various socio-economic conditions to provide a more comprehensive understanding of this phenomenon.

CONCLUSION

The present study aimed to investigate the various factors influencing farmers' Behavioral Intentions (BI) to adopt Internet of Things (IoT) technologies in agriculture. Employing the Unified Theory of Acceptance and Use of Technology (UTAUT) framework, the research found significant predictors that align with both the theoretical model and empirical findings in different sectors and geographical contexts. Firstly, Performance Expectancy (PE) and Effort Expectancy (EE) were validated as critical drivers for the adoption of IoT technologies among farmers. These findings are consistent with previous research, and they highlight the importance of perceived benefits and ease of use in technology adoption. Social Influence (SI) also emerged as a significant, yet complex predictor, indicating that external opinions and societal norms have a role but may vary in their impact depending on contextual factors. Facilitating Conditions (FC) were confirmed to significantly affect BI, emphasizing the need for an enabling environment for technology to be readily adopted. In addition, Hedonic Motivation (HM), often an overlooked factor, was found to be significant, suggesting that the intrinsic enjoyment derived from using a technology could be a crucial motivator for its adoption. On the other hand, Price Value (PV) was not found to be a significant predictor, challenging some existing literature and indicating that cost may not be a significant barrier to IoT adoption for farmers in this specific demographic. Lastly, Habit (HT) was also identified as a significant predictor of BI, aligning with other sectors like fintech. This suggests that established behaviors and routines in technology use significantly affect the adoption of new technologies. The study contributes to filling research gaps by extending these insights to the agricultural sector within the Ghanaian context. It provides valuable information for policymakers, stakeholders, and technology developers in understanding the dynamics of technology adoption in agriculture. Strategies aiming to foster technology adoption should consider these predictors to tailor interventions that resonate with farmers' needs, perceptions, and established habits.

IMPLICATIONS OF THE STUDY FOR THEORY, LITERATURE, POLICY RELEVANCE PRACTICE AND SOCIAL IMPACT

Theory

The study extends the Unified Theory of Acceptance and Use of Technology (UTAUT) to the agricultural sector in a Ghanaian context, enriching the theoretical framework with nuanced insights. It confirms the significance of established predictors like Performance Expectancy (PE) and Effort Expectancy (EE) in a new demographic, thereby reinforcing the universality and adaptability of the UTAUT model. It also complicates our understanding of Social Influence (SI), suggesting that its impact may vary depending on contextual factors, which opens avenues for further theoretical exploration.

Literature

This research serves to fill existing gaps in literature by applying the UTAUT framework to the agricultural sector in Ghana, a demographic and geographical area that had previously been less explored. It adds empirical evidence to existing literature on the significance of Facilitating Conditions (FC) and Hedonic Motivation (HM) in technology adoption. Furthermore, the study provides a counter-narrative to the commonly held belief that Price Value (PV) is a significant predictor of adoption, thus encouraging further scholarly debate and investigation.

Policy Relevance

The findings of this study have significant policy implications. For instance, the role of Facilitating Conditions (FC) emphasizes the need for policymakers to create an enabling environment for the adoption of IoT technologies. This could mean investing in infrastructure, providing training programs, and offering technical support. Additionally, the insignificance of Price Value (PV) as a predictor suggests that policy focus may need to shift away from merely subsidizing costs to enhancing perceived benefits and ease of use.

Practice

From a practical standpoint, technology developers and agricultural extension services should consider these predictors when designing and implementing IoT solutions for farmers. Emphasizing the ease of use and tangible benefits could enhance adoption rates. Moreover, developing training programs that create a sense of enjoyment and engagement (HM) could be an innovative strategy to foster technology acceptance.

Social Impact

Understanding the factors that drive or inhibit technology adoption can have a transformative social impact, particularly in sectors like agriculture that are central to livelihoods and food security. The findings can inform community outreach and educational programs, making them more effective in encouraging technology adoption. By focusing on key predictors like PE, EE, and HM, interventions can be designed to resonate with farmers' needs and social contexts, thereby accelerating the adoption of technologies that can improve agricultural outcomes and, by extension, livelihoods.

RECOMMENDATIONS

Academic and Theoretical Implications

The study underscores the need for further academic inquiry, particularly focusing on the complex role of Social Influence (SI) in technology adoption. The varying impact of SI on Behavioral Intentions (BI) suggests that contextual factors could be at play, requiring more nuanced research methodologies. Additionally, given that Price Value (PV) was not a significant predictor in this agricultural context, it would be beneficial for future studies to explore this relationship in different socio-economic environments. Extending the study to different demographics and sectors could also provide a more comprehensive understanding of technology adoption drivers.

Policymakers and Governance

The findings of the study hold significant implications for policymakers, especially in the agricultural sector. The critical role of Facilitating Conditions (FC) suggests that investments in infrastructural development and technical support could have a profound impact on technology adoption rates. Moreover, the significance of Effort Expectancy (EE) implies that training programs aimed at simplifying the use of IoT technologies could be highly effective. Policymakers should also consider leveraging community leaders to advocate for technology adoption, given the proven influence of Social Influence (SI).

Practitioners and Industry

For technology developers and industry stakeholders, the study offers valuable insights into user adoption behaviors. The importance of Effort Expectancy (EE) suggests that a focus on user-friendly design could be a game-changer in technology adoption. Marketing strategies should emphasize the performance benefits of IoT technologies, aligning with the significant role of Performance Expectancy (PE) in adoption. To capitalize on the role of Hedonic Motivation (HM), providers might consider implementing engagement strategies like gamification to make the user experience more enjoyable.

Social and Community Impact

Community leaders and social organizations can use these findings to guide their initiatives. Given the importance of Performance and Effort Expectancies, awareness campaigns should be designed to focus on these aspects. Skill-building workshops could be an effective way to create facilitating conditions, making the technology more accessible to potential users.

General Recommendations

A more holistic approach to encouraging technology adoption seems warranted, one that combines the significant predictors identified in this study. Given the multiple factors influencing adoption, a multi-faceted strategy could be the most effective. Longitudinal studies are also recommended to assess the sustainability and long-term impact of these technologies on the agricultural sector and beyond.

LIMITATIONS AND FUTURE RESEARCH DIRECTION

Limitations of the Study

While the study offers valuable insights into the factors affecting the adoption of IoT technologies among farmers, it is not without limitations. One significant constraint is the geographical scope of the research, which focused on the Ghanaian context. This geographical focus may limit the generalizability of the findings to other cultural or economic settings. Additionally, the study did not delve into the moderating effects of variables such as age, education, or experience, which could provide a more nuanced understanding of technology adoption. Another limitation lies in the methodological approach. While the study effectively employed structural equation modeling to analyze relationships between variables, the cross-sectional nature of the research offers only a snapshot in time. It doesn't capture the dynamic nature of technology adoption, which could be influenced by rapidly changing external factors like technological advancements or shifts in policy. Furthermore, the study did not explore the reasons behind the lack of significance for Price Value (PV) in the context of IoT adoption among farmers. This could be an area where qualitative insights might add value to the quantitative data, helping to explain this unexpected finding.

Future Research Directions

Given these limitations, several avenues for future research emerge. Firstly, similar studies could be replicated in diverse geographical and cultural settings to test the generalizability of the findings. Comparative studies could offer insights into how different cultural or economic contexts influence the factors affecting technology adoption. Secondly, future research could look at incorporating more variables, including moderating and mediating factors, to provide a richer understanding of technology adoption. Factors such as farmers' prior experience with technology, levels of education, and socio-economic conditions could be examined for their potential impact. Thirdly, longitudinal studies would be beneficial to understand the sustainability and long-term impacts of IoT technology adoption among farmers. This could help policymakers and stakeholders make more informed decisions about resource allocation for technology implementation and training programs. Lastly, qualitative research methods, such as interviews or focus groups, could be employed to delve deeper into some of the unexpected findings of this study. For instance, understanding why Price Value (PV) was not a significant factor could offer valuable, context-specific insights that quantitative methods may not fully capture.

Conflict of Interest Statement

The Authors hereby declare that there are no potential conflicts of interest regarding the research.

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