Assessment of Farmers' Acceptance of Intelligent Agriculture System using Technology Acceptance Model

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ABSTRACT

Several known factors are hampering the acceptance of technology-enhanced farming practices such as precision agriculture and smart farming in developing countries. These factors include high initial cost, low access to technology infrastructure, unawareness of efficient technology use in farming and socio-cultural issues. As a result, farmers in many developing countries rely purely on traditional farm management methods. Unfortunately, these traditional practices are faced with several challenges such as the inability to predict adverse conditions before they occur. Besides such methods are suitable for small-scale farms. Technology-enhanced farming practices have been proven by research and reported as a means of improving farm management and agriculture yield in many advanced economies. This study presents the use of the Technology Acceptance Model (TAM) to assess farmers' acceptance level of technology-enhanced farming practices in Tarkwa Nsuaem Municipality; an important mining district in Ghana. The proposed model was empirically tested using data collected from a survey of three hundred and forty (340) farmers in mining communities within the municipality. Structural equation modelling was used as the statistical technique to analyze the data to explain the acceptance. The general structural equation model, which includes perceived usefulness, perceived ease of use, attitude, and behavioural intention to use an intelligent agricultural system by farmers was developed based on TAM. The result proved that farmers' perception of the ease of use of technology significantly impacts their perception of its usefulness in farming. It further showed that farmers' intention to use technology for farm management would depend on their attitude towards its use. The model would provide the major stakeholders of agriculture with implications for the effective implementation of an intelligent agriculture system.

General Terms

Intelligent Agriculture Systems, Information Technology, Modeling

Keywords
Precision Agriculture, Smart Farming, Attitude, Technology Acceptance Model, Structural Equation Modeling.

1. INTRODUCTION
Information Technology (IT) continues to successfully impact various dimensions of agriculture such as farm conditions management, farm machinery enhancement and storage and distribution of farm products. The great strides IT is making in the field of agriculture have largely been achieved through concepts such as precision agriculture and smart farming. The advent of Data Analytics, Machine Learning, the Internet of things and Mobile Applications Development has largely been identified as strong driving forces fueling the successful design and implementation of many precision agriculture and smart farming Systems.

The concept of precision agriculture relies on the use of advanced technologies such as Global Positioning System (GPS), Geographic Information Systems (GPS), Remote Sensing and Variable Rate Technology to optimize and improve farm yield [1],[18],[28],[39],[40]. The farm management process is improved through automated, precise, and effective fertilizer application, smart irrigation, and waste reduction amongst others.

The concept of smart farming, (alternatively known as Agriculture 4.0), has a similar focus as precision agriculture of improving farm productivity, sustainability, and management efficiency. Smart farming, however, has a broader focus, as it encompasses a wider range of technologies and innovations for managing the complete lifecycle of the agricultural production process. The focus of smart farming is achieved through the creation of an interconnected farming ecosystem with the help of technologies including, but not limited to Artificial Intelligence, Machine Learning, the Internet of Things, Blockchain, Cloud Computing, Drones and Robots [14],[20],[22],[38].

Despite the known advantages of precision agriculture and smart farming, they are least practiced in many developing countries. This is attributed to a myriad of reasons. The International Food Policy Research Institute reports high initial costs as a barrier to the use of these technology-enhanced farming practices [19]. A second major factor hampering precision agriculture and smart farming in many developing countries is low access to digital infrastructure [37]. Thirdly, a lack of education and unawareness of the use of digital tools to improve agricultural yield has also been reported as a key reason for the low acceptance of precision agriculture and smart farming [27]. In addition, research in India demonstrated socioeconomic factors as a reason why many old folks may not want to accept advanced technology in agricultural practices [32].

This paper contributes to the existing body of knowledge regarding the reasons for the low acceptance of precision agriculture and smart farming. For easier referencing, we adopt the term "intelligent agriculture" to mean precision agriculture and smart farming for the rest of the paper. The paper uses the Technology Acceptance Model to predict farmers' acceptance of intelligent agriculture systems in Tarkwa-Nsuaem Municipality; a popular mining district in the Western Region of Ghana. The region is made up of agricultural districts with the majority of its vegetation within the high forest zone of

Ghana characterized by moderate temperatures and the wettest part of Ghana with an average rainfall of 1600 mm per annum [3]. The major crops are maize, cassava, plantain, yam, cocoyam, rice, cocoa, coconut, rubber, oil palm and coffee.

This study proposes an integrated theoretical framework for assessing farmers' acceptance of intelligent agriculture systems and the intention to use them based mainly on the technology acceptance model. The specific objectives of the study are to:

(i) analyze the relationship between farmers' intention to use the intelligent agriculture system with selected constructs such as their attitude, perceived usefulness, and perceived ease of use of an intelligent agriculture system;

(ii) develop a structural equation model to assess the acceptance of an intelligent agriculture system amongst farmers in the selected district.

1.1 Research Hypotheses

Based on the stated objectives and the reviewed literature, this study tested the following hypotheses:

- **H1:** *Perceived usefulness would have a significant effect on farmers' attitudes toward the use of the intelligent agriculture system.*
- **H2:** *Farmers' attitudes toward the use of the Intelligent Agriculture System would have a significant effect on their behavioural intentions to use.*
- **H3:** *Perceived ease of use of the intelligent agriculture system would have a significant effect on perceived usefulness.*
- **H4:** *Perceived ease of use of the intelligent agriculture system would have a significant effect on farmers' attitudes toward use.*

1.2 Theoretical Framework

TAM, introduced by Davis in 1986, is a well-known model to evaluate the acceptance and usage of technology. TAM has proven to be a viable and potent theoretical model to predict and explain user behaviour in accepting and using new technology [9],[21],[24]. TAM provides the foundation for analysing how external variables influence attitudes, beliefs, and intentions to use technology. Perceived usefulness and perceived ease of use are the two (2) beliefs that the TAM stands on [8],[25],[26],[35].

According to [8], the TAM evaluation of one's actual use of a technology system is influenced directly or indirectly by the user's behavioural intentions, attitude, perceived usefulness of the system, and perceived ease of use of the system. TAM also considers that external factors have an impact on intention and actual use through the effects on perceived usefulness and perceived ease of use as shown in Figure 1.

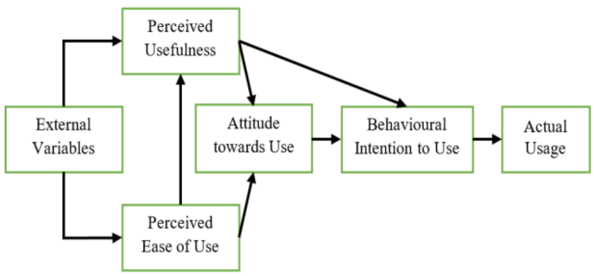


Figure 1: The Original Technology Acceptance Model (Source: Davis,1989)

TAM has undergone modification over time and has resulted in an updated model called TAM2. According to [36], TAM2 enhanced the original model proposed by [8] in 1989 to explain perceived usefulness and usage intentions including social influence (subjective norm, voluntariness, and image), cognitive instrumental processes (job relevance, output quality, and result demonstrability) and experience. This study adopted the original TAM proposed by [8].

Several studies have examined TAM as a model to explain how people adopt and use technology. In a study conducted by,[6] to predict students' intention to adopt mobile learning by applying the structural equation model method for the analysis of data, he concluded that "TAM was fairly able to predict and explain behavioural intention among students. The study also found that attitudes toward the use and subjective norm significantly influenced students' behavioural intention to use mobile learning".

[31] did similar research with TAM to investigate web-based learning. Using the structural equation modelling techniques, he tested the relationships between perceived usefulness, perceived ease of use and intention to use with university students. He found that "the model fit the collected data and that the usefulness and ease of use turned out to be good determinants of the acceptance and use of a course website as an effective and efficient learning technology." [31] further argued that perceived usefulness can be defined as the extent to which a university student believes using e-learning will boost his or her learning.

TAM has been used as the main model for several studies including, understanding the motivations to use online streaming services [7]; perceived usability and self-efficacy in teachers' technology acceptance [15]; the factors influencing artificial intelligence-based intelligent products [33] and early childhood teachers' technology acceptance levels [29]. Though TAM was initially proposed to explore the acceptance of technology in commercial and business settings, it is now a useful model for many others [4],[11].

Even though TAM has extensive use there are many challenges which have been found with the use of TAM.[4] argued that TAM is an oversimplified model. [10] were of the view that more research is needed to increase the external validity of TAM. According to [15], one major limitation of TAM is that it lacks emphasis on the system characteristics, which may influence user acceptance, as in usability evaluations. In a study conducted by [21], it was acknowledged that TAM is a valuable model and emphasised the significance of integrating TAM into other models, incorporating variables related to both human and social change processes. They also stress the importance of adopting an innovative model to ensure comprehensive coverage of TAM.

2. MATERIALS AND METHODS USED

2.1 Research Design

This study used primary data based on the conceptual framework of TAM and the deductive approach. The deductive approach needs huge data for generalization purposes, so the results obtained from the study would be used to generalize the views of farmers in the mining communities of Ghana.

The convenience sampling technique was used to collect data for this study because it is widely preferred for quantitative studies by researchers [12]. "Convenience sampling is a type of non-probability sampling where respondents can be selected based on their easy accessibility and willingness to complete the questionnaires" [13]. The target population for this study was clearly defined, therefore, the respondents were farmers from a mining community and are estimated to be around 340 respondents. The questionnaires were distributed specifically to the target population.

2.2 Instrument Design

The survey instrument comprised six (6) sections designed by the researchers per the objectives of the study and the literature reviewed on TAM. The questionnaires were distributed to 340 farmers (large and small scale). The first section contained questions to collect demographic information. The second section contained questions to assess the awareness of farmers of the intelligent agriculture system concept. The other sections contain eighteen (18) statements on the four (4) constructs for the study. The constructs were perceived usefulness, perceived ease of use, attitudes toward use and behavioural intention to use. The constructs on perceived usefulness, perceived ease of use and behavioural intention to use [8]. A 5-point Likert-scale measurement ranging from 1 (strongly disagree) to 5 (strongly agree) was used for sections 3 to section 6 of the questionnaire.

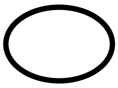
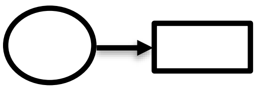
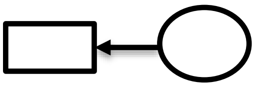
2.3 Structural Equation Modelling

Structural equation modelling (SEM) is a statistical modelling approach suitable for testing hypotheses about relations among observed and latent variables [16]. Such relations are mostly linear [23][30]. Whereas observed variables may be measurable using surveys, latent variables are not measurable. Examples of latent variables are quality of life, sound mind, greatness etc. The relations estimated by [34] outline the following as the two main goals of SEM:

1) to understand the patterns of correlation/covariance among a set of variables and
2) to explain as much of their variance as possible with the model specified.

SEMs are usually modelled diagrammatically using the notations shown in Table 1 [34].

Table 1. Notations of SEM diagram

Symbol	Name/Meaning
	Latent/unmeasured variable
	Measured/observed/ Manifest variable
	direct relationship indicating the cause
	Correlation
	The error associated with measured/ observed/Manifest variable
	path coefficient for regression of a latent variable on an observed variable

Typically, a composite or full SEM consists of a measurement model which describes the relationships between observed variables and the construct and a structural model which describes interrelationships among constructs [2]. The basic structure of a composite SEM (adapted from [2]) is given in Figure 2.

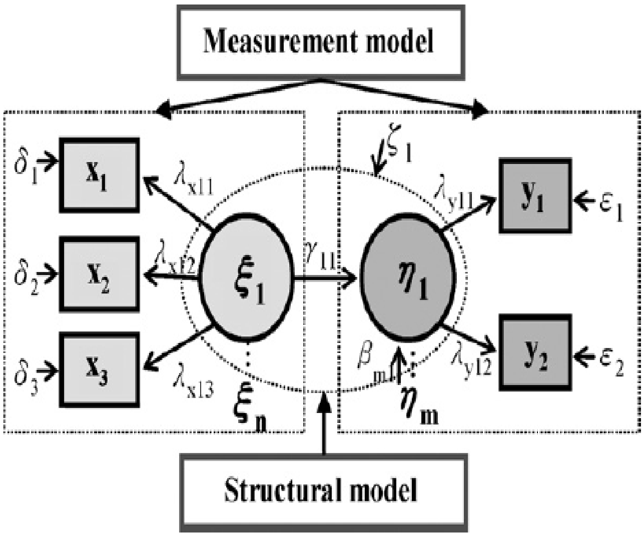


Figure 2: The Basic Structure of a Composite SEM

Where,

X -	Vector of observed exogenous variables
Y -	Vector of observed endogenous variables
ξ -	Vector of latent exogenous variables
η -	Vector of latent observed endogenous variables
δ -	Vector of measurement error terms for observed variables *X*
ε -	Vector of measurement error terms for observed variables *Y*
λ -	Coefficient of observed variables
ζ -	Vector of the error terms in the structural model
β -	Coefficient of expected changes after a unit increases in η or ξ

The measured model and the structural model are respectively given in equations 1 and 2 [2].

$$X_{1,\ldots,n} = \lambda_{x1,\ldots,x_n} \ \xi_{1,\ldots,n} + \delta_{1,\ldots,n}$$
$$Y_{1,\ldots,n} = \lambda_{x1,\ldots,y_n} \ \eta_{1,\ldots,n} + \varepsilon_{1,\ldots,n} \qquad (1)$$

$$\eta_{1,\ldots,n} = Y_{y1,\ldots,y_n} \ \xi_{1,\ldots,n} + \zeta_{1,\ldots,n} \qquad (2)$$

2.4 Statistics of SEM

There are several statistical tests required to determine the adequacy of model fit to the data. The following are some relevant tests:

(a) Chi-square tests: This statistic computes the difference between expected and observed covariance matrices. It is computed as shown in equation 3.

$$x^2 = \frac{\sum(O_i - E_i)^2}{E_i} \qquad (3)$$

Where: O_i is the observed value and E_i is the expected value. The closer the value of x^2 to zero, the better the model fit and the probability level must be greater than 0.05.

(b) The Comparative Fit Index (CFI): this statistic is defined by [5] as an "index to summarize the relative reduction in the non-centrality parameter of two nested models". This statistic is defined by equation 4.

$$CFI = 1 - \frac{x_m^2 - df_m}{x_b^2 - df_b} \quad (4)$$

Where the chi-square value of the model of interest, x_b^2 is the chi-square value of the baseline model while df_m and df_b are the degrees of freedom of the model of interest and the baseline model respectively. CFI ranges from 0 to 1 with a larger value indicating a better model fit. A CFI value must be 0.90 or higher to be acceptable [17].

(c) Root Mean Square Error of Approximation (RMSEA): RMSEA values range from 0 to 1. Smaller RMSEA values indicate better model fit. Acceptable model fit is indicated by an RMSEA value of 0.06 or less [17]. This statistic is computed as shown in equation 5.

$$RMSEA = \frac{\sqrt{(x^2 - df)}}{\sqrt{df[(N-1)]}} \quad (5)$$

Where N is the sample size and df is the degrees of freedom of the model and x^2 is the chi-square value.

3. RESULTS AND DISCUSSIONS

3.1 Descriptive Statistics

The respondents consisted of about 69% male and 31% female. The majority (72.2%) were in the age group 21 to 30. The respondents were single crop, mixed crop, animal, fish and mixed (animal and crop) farmers. Mixed crop farmers were 27.8% being the highest. Most (about 91.7%) of the respondents practiced small-scale farming. The respondents' knowledge of Intelligent Agriculture is shown in Figure 3.

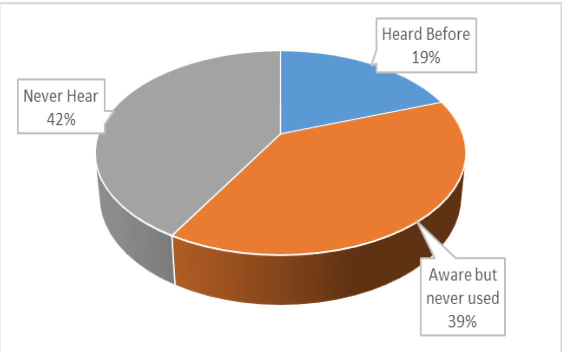


Figure 3: Knowledge of Intelligent Agriculture

3.2 SEM Model of TAM to Test Acceptance of Intelligent Agriculture

In line with the hypotheses, the following constructs were formulated to test the level of acceptance of intelligent agriculture. Each construct was measured on a scale of 1 to 5.

(i) 1 = "strongly disagree"
(ii) 2 = "Disagree"
(iii) 3 = "Neutral"
(iv) 4 = "Agree"
(v) 5 = "Strongly agree"

The constructs are given in Table 2.

Table 2. The Constructs for the Study

Construct	
Perceived Usefulness	
PU1:	Using this system in my job would enable me to accomplish tasks more quickly.
PU2:	Using this system would improve my job performance.
PU3:	Using this system would increase my productivity.
PU4:	Using this system would enhance my efficiency and accuracy.
PU5:	Using this system would make my work easier.
PU6:	This system would be useful in my job.
Perceived Ease of Use	
PEOU1:	Learning to operate this new system would be easy for me.
PEOU2:	I would find it easy to get this system to do what I want it to do.
PEOU3:	My interaction with the system would be clear and understandable.
PEOU4:	I would find the system clear and understandable.
PEOU5:	It would be easy for me to master the use of this system.
PEOU6:	I would find the system easy to use
Attitude towards Use	
ATU1:	I am looking forward to using this system to do aspects of my work that require it.
ATU2:	I like working with technology that supports my work.
ATU3:	I am willing to use any new technology that supports my work.
ATU4:	I have a positive feeling toward the use of this system.
Behavioural Intention to Use	
BIU1:	I intend to continue to use this system in the future.
BIU2:	I expect that I will use this system in the future.
BIU3:	I plan to use this system in the future.

The SEM model was created using the constructs outlined in table 2 and driven by the collected data. The model is given in figure 4. The model was created using IBM SPSS Amos. The first step in this process was to define the variables in the data by their respective types (continuous, categorical, etc) in SPSS. Secondly, the physical structure of the model was created from Amos graphics window in conformance with the constructs stated in table 2. The third step in the process was to specify the model relationships and set all necessary parameters. Finally, the model was run and assessed for accuracy using standard indices like the chi-square.

3.3 Model Fit Analysis

The model was estimated using the Maximum Likelihood method and adjusted to improve fitness with x^2 value of 343.17 and a probability and degree of freedom being 0.0 and115 respectively. Other important indices of finesses of our model such as the Goodness of Fitness Index and Normed Fitness Index are given in Table 3.

3.4 Hypotheses Testing

The hypotheses were tested based on the standardized estimates given in Table 4. PEOU--->PU and ATU--->BIU were found significant by the maximum likelihood estimates while paths PEOU--->ATU and PU--->ATU were not. Per these observations, hypotheses H2 and H3 are supported while the other two do not hold.

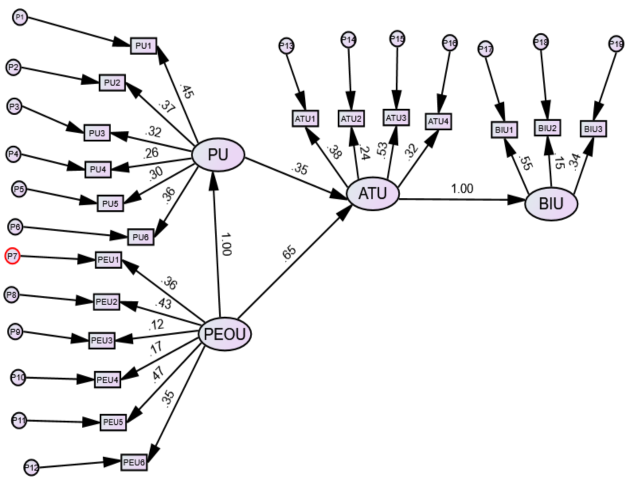


Figure 4: Graphical Representation of the Developed Model

Table 3. Model Fit Index

Index	Model output	Threshold	Observation
GFI	0.918	>0.90	Good fit
CFI	0.905	>0.90	Good fit
RMSEA	0.077	<0.08	Good fit
NFI	0.866	>0.90	Close to a Good fit
X^2/df	2.984	<5	Good fit

The low acceptance of intelligent agriculture practices in the district is, therefore, due to a lack of knowledge of the ease of use of such technologies to enhance farm yields. Therefore, farmers would accept Intelligent Agriculture (IA) as a useful practice if they are convinced of its ease of use. Any attempt to implement Intelligent Agriculture in the Tarkwa-Nsuaem Municipality, therefore, needs to first demonstrate that, Intelligent Agriculture is easy to use. This finding resonates well with the works of [27] and [32] published in 2022 and 2024 respectively. Per these findings, once farmers are convinced about the ease of use of Intelligent Agriculture, they are likely to accept it as a useful practice.

Secondly, the farmers' intention to use this new technology, would depend on their attitudes towards its use. Hence, farmers' attitudes towards this technology, which may have socio-cultural underpinning may also need to be worked on for successful acceptance and use of intelligent agriculture. It is therefore necessary for stakeholders to launch education and awareness campaigns to educate farmers to accept technology as a useful tool for effective large-scale farming.

Table 4. Model Estimates Summary

Path direction	Standardized Estimates	Observation
PEOU --->PU	1.000 ***	Significant
PEOU --->ATU	0.746	Insignificant
PU --->ATU	0.254	Insignificant
ATU --->BIU	1.000 ***	Significant

4. CONCLUSION

Using the Technology Acceptance Model, this paper focused on testing farmers' level of acceptance of Intelligent Agriculture in the Tarkwa-Nsuaem Municipality. The Model helped to understand the key determinants that would influence farmers' adoption of Intelligent Agriculture systems. The final results of the study identified the main critical success factors that need to be considered when an organisation is planning to introduce any kind of Intelligent Agriculture system to farmers in the Tarkwa-Nsuaem Municipality. The study established that the strongest critical factors were farmers' intention to use Intelligent Agriculture Systems have a significant effect on their behavioural intentions to use and their perceived ease of use of the intelligent agriculture system would have a significant effect on the perceived usefulness of intelligent agriculture systems.

As a result of the established significance of the need for farmers to accept and use Intelligent Agriculture systems, it is recommended that further research should be done to explore additional factors that could influence their acceptance. A modification of the Technology Acceptance Model to include the actual usage of a prototype Intelligent Agriculture System could provide valuable insights into the practical application and acceptance of Intelligent Agriculture systems. This approach could offer a comprehensive understanding of the farmers' perceptions and behaviours towards adopting Intelligent Agricultural systems.

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