Evaluation of Rice Farmers' Acceptance of a Knowledge Management System using the Technology Acceptance Model

George Essah Yaw Okai[1], Raphael Olufemi Akinyede[2], Millicent Agangiba[3], William Akotam Agangiba[4]
[1]Department of Computer Science and Engineering, University of Mines and Technology, Tarkwa, Ghana
[2] Department of Information Systems, Federal University of Technology, Akure Ondo State, Nigeria
[3] Department of Information Technology Studies, University of Professional Studies, Accra, Ghana
[4] School of Information Technology, University of Cincinnati, Cincinnati, Ohio, USA

ABSTRACT
This study evaluates the level of acceptance of a Knowledge Management System (KMS) designed to support intelligent rice farming practices, using the Technology Acceptance Model (TAM). Data from 315 rice farmers in Afere, Ghana, were analysed using Structural Equation Modelling (SEM) to determine how perceived usefulness (PU) and perceived ease of use (PEOU) influence attitudes toward use (ATU), behavioural intention to use (BIU), and actual system usage (ASU). The findings demonstrate that PEOU significantly impacts PU and ATU, which subsequently drive BIU and ASU. Findings indicate that enhancing usability and fostering positive user attitudes can significantly increase KMS adoption by rice farmers. This study provides valuable insights for improving the effectiveness and acceptance of technology-driven solutions in agricultural communities.

General Terms
Evaluation, Information Technology, Modelling

Keywords
Technology Acceptance Model, Structural Equation Modelling, Knowledge Management System, System Evaluation

1. INTRODUCTION
The agricultural sector faces significant challenges in sharing and managing knowledge [37], necessitating innovative approaches to knowledge dissemination. Knowledge Management Systems (KMS) can present a solution, offering tailored, timely information. This study evaluates rice farmers' level of acceptance of a KMS designed to support the dissemination of knowledge for intelligent farming practices, using TAM as the theoretical framework. The research focuses on the Afere rice farming community, where the prototype KMS was implemented. By exploring TAM constructs such as PU, PEOU, ATU, BIU, and ASU, this study aims to provide insights into factors influencing technology adoption among rice farmers.

Understanding KMS requires a foundational grasp of the concepts of data, information, and knowledge. Data represents raw, unprocessed facts, such as numbers or characters, which lack inherent meaning. When processed and contextualised, data transforms into information that is relevant and purposeful.

Knowledge, as defined by [1], is a dynamic mix of experiences, values, contextual insights, and intuition that is shaped by individual and organisational experiences. This knowledge can be embedded in routines, practices, or documents, making it a cornerstone of decision-making and innovation within organisations. Hence, the conversion of data into information and subsequently into knowledge underscores the essence of KMS.

In Knowledge Management (KM), knowledge is broadly categorised into explicit and tacit forms. Explicit knowledge is codified, easy to document, and readily accessible in databases, memos, and documents [2]. It represents the primary type of knowledge managed by KMS. On the other hand, tacit knowledge is deeply personal and rooted in experiences, intuition, and expertise, making it challenging to document or transfer [2]. This distinction is vital in designing KMS, as explicit knowledge aligns with technology-driven systems, while tacit knowledge demands a focus on human interactions and collaboration to facilitate its transfer and application effectively.

KMS integrates KM principles with technology to enable the systematic collection, storage, retrieval, and sharing of knowledge within organisations. These systems enhance decision-making, improve efficiency, and foster collaboration by ensuring that information and knowledge are readily accessible to stakeholders [3]. Modern KMS encompass various types, such as Document Management Systems, Business Intelligence Systems, and Learning Management Systems, tailored to specific organisational needs. By leveraging these systems, organisations can achieve strategic objectives, enhance competitive advantage, and support innovation. Thus, a well-implemented KMS not only facilitates knowledge flow but also bridges the gap between human expertise and technological efficiency, underscoring its critical role in contemporary organisations, including agriculture.

Knowledge sharing in Ghana's agricultural sector is significantly hindered by infrastructural and technological limitations, particularly in rural areas where access to basic communication networks remains inadequate [20][21][31]. These challenges are further exacerbated by low levels of formal education among farmers, which restricts their ability to acquire, process, and disseminate agricultural knowledge effectively [31]. Additionally, a lack of incentives for knowledge sharing presents another critical barrier, as many farmers perceive agricultural knowledge as a competitive advantage and are reluctant to share insights with others, especially potential competitors [21]. Cultural and linguistic diversity in Ghana further complicates knowledge dissemination, as language barriers and ethnic differences often impede effective communication and collaboration among farmers and agricultural stakeholders [31].

Addressing these challenges is essential for enhancing agricultural productivity and fostering sustainable development in Ghana. A concerted effort from key stakeholders, including the government, non-governmental organisations, agricultural extension agents, and farmers, is necessary to create an enabling environment for knowledge sharing. This could involve investing in rural infrastructure, expanding access to communication technologies, and implementing targeted educational programs to enhance farmers' capacity to engage with modern farming practices. Furthermore, fostering a culture of collaboration through policy interventions and incentive structures could encourage farmers to share knowledge more openly. By overcoming these barriers, Ghana's agricultural sector can achieve greater efficiency, resilience, and long-term sustainability [20][21][31].

This study presents an integrated theoretical framework for evaluating rice farmers' acceptance and intended utilisation of a KMS designed to support the dissemination of knowledge for intelligent rice farming. This study is primarily grounded in the Technology Acceptance Model (TAM) and aims to:

(i) Examine the relationship between farmers' intention to adopt the KMS and key determinants, including attitude, perceived usefulness, and perceived ease of use;

(ii) Develop a structural equation model (SEM) to systematically evaluate the factors influencing KMS acceptance among rice farmers.

1.1 Review of Related Works

The Technology Acceptance Model (TAM) is a widely recognised framework in Information Systems (IS) research, designed to explain and predict an individual's acceptance and use of technology. Developed by Davis in 1986 and refined in 1989, TAM theorises that actual technology usage is influenced by behavioural intention, which is, in turn, shaped by perceived usefulness and perceived ease of use. Perceived usefulness refers to the extent to which users believe that using a specific system will enhance their performance, while perceived ease of use reflects the effort expected to operate the system [4][5][6]. External factors, such as social, cultural, and political influences, also impact these perceptions, making TAM a versatile and dynamic tool for analysing user attitudes and behaviours toward technology adoption [6].

Over the years, TAM has evolved through significant modifications and extensions to enhance its explanatory power. [7] proposed a combined TAM-TPB model integrating the Theory of Planned Behaviour (TPB), while [8] introduced TAM2, which incorporates variables such as social influence and cognitive processes. Other researchers have contributed additional dimensions, such as peer influence [9] and trust and perceived risk [10], to address specific contexts, including healthcare, e-commerce, and online banking. These adaptations highlight TAM's adaptability to diverse technological and cultural settings, reinforcing its status as a reliable framework for understanding technology acceptance.

Numerous empirical studies underscore the utility of TAM across different domains. A study by [11] evaluated the acceptance of web-based learning and demonstrated that perceived usefulness and ease of use are critical determinants of user intention. Similarly, [12] applied TAM to predict students' adoption of mobile learning, finding that attitudes and subjective norms significantly influence behavioural intentions. Other studies have explored TAM's applicability to emerging technologies, such as artificial intelligence-based products [13] and intelligent systems in education [14]. These evaluations affirm TAM's robustness in explaining user behaviour across both traditional and contemporary technological environments.

Despite its strengths, TAM has faced criticism for its limitations. Scholars like [15] argue that TAM oversimplifies the complex processes involved in technology acceptance, while [16] and [17] call for enhanced external validity. An exploratory study by [18] critiques TAM's insufficient focus on system characteristics, such as usability, significantly influencing acceptance. To address these gaps, [19] recommends integrating TAM with other models, incorporating human and social dynamics variables, and adapting it to broader innovation contexts. These recommendations suggest avenues for further refinement and expansion of TAM to address its shortcomings.

TAM remains a foundational framework for studying technology adoption and user behaviour in Information System research. Its core constructs of perceived usefulness and perceived ease of use provide a valuable lens for understanding acceptance across diverse settings. While TAM has been extensively validated and extended to fit various contexts, ongoing efforts to enhance its comprehensiveness and applicability are crucial for addressing its limitations. This continuous evolution ensures TAM's relevance as a robust tool for exploring the dynamic interplay between technology, users, and the environments in which they operate.

1.2 Research Hypotheses

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

(i) **H1:** *Farmers' perceived usefulness (PU) of the KMS has a significant effect on their attitudes toward its use (ATU). (PU→ATU)*

(ii) **H2:** *Farmers' attitudes toward the use of the KMS have a significant effect on their behavioural intentions to use (BIU).*
(ATU→BIU)

(iii) **H3:** *Farmers' perceived ease of use (PEOU) of the KMS significantly affects perceived usefulness (PU).*
(PEOU→ PU)

(iv) **H4:** *Farmers' perceived ease of use of the KMS significantly affects farmers' attitudes toward use.*
(PEOU→ATU)

(v) **H5:** *Farmers' behavioural intentions to use the KMS have a significant effect on their Actual System Use (ASU).*
(BIU→ASU)

Based on the hypotheses stated, a conceptual graphical model of the proposed system, as shown in Figure 1, was designed to represent each variable and the links between them. This proposed model was used for the SEM.

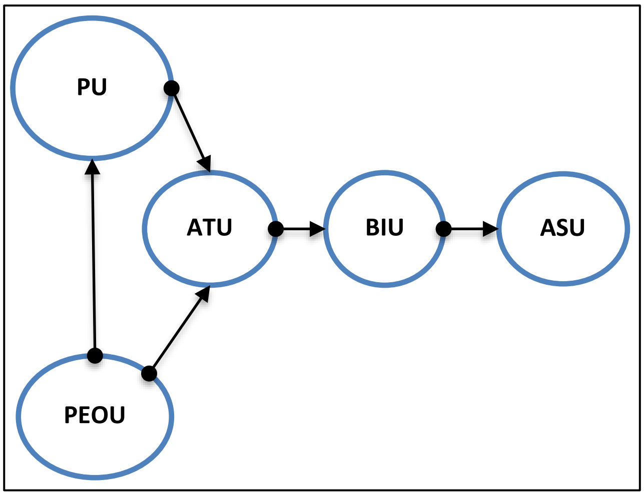


Figure 1:Proposed research model for evaluating KMS acceptance.

2. MATERIALS AND METHODS USED

2.1 Research Design

This study employed a methodological framework grounded in TAM, using a deductive approach to evaluate behavioural intentions among rice farmers on the adoption and use of KMS in the Afere rice farming community of Ghana. Given the deductive methodology's reliance on extensive datasets to facilitate generalisable conclusions, the research aimed to extrapolate findings to the broader population of rice farmers within the specified region. A convenience sampling technique, a non-probability method characterised by the selection of participants based on accessibility and willingness to be engaged [33], was adopted because it is widely preferred for quantitative studies by researchers in quantitative research paradigms [32]. The target population was 315 rice farmers from Afere. The questionnaires were distributed only to the target population.

For this study, a prototype KMS was designed, implemented, and shown to the targeted population. The KMS was an Android-based mobile application customised to store and share knowledge on intelligent rice farming practices. It was purposefully designed to provide user-friendly information retrieval and search functionalities, featuring an intuitive, graphical user interface. Additionally, the system incorporated fairly robust security measures and access control mechanisms to ensure data integrity and protect user privacy.

2.2 Instrument Design

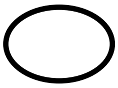
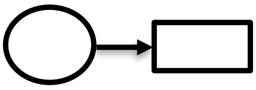
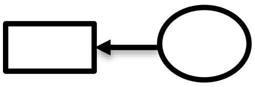
The survey instrument was a questionnaire consisting of eight sections designed by the researchers to align with the study's objectives and the literature on TAM. The questionnaires were distributed to 315 rice farmers. The first section gathered demographic information, while the second section explored the challenges faced by rice farmers. The third section assessed farmers' awareness of the KMS concept.

The remaining sections included twenty-one statements related to five key constructs: perceived usefulness, perceived ease of use, attitudes toward use, behavioural intention to use, and actual use[22]. Sections four through eight of the questionnaire used a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

2.3 Structural Equation Modelling

Structural Equation Modelling (SEM) is a sophisticated statistical technique that enables researchers to analyse relationships between latent and observed variables, facilitating the examination of complex causal structures. As a multivariate analysis method, SEM allows for the simultaneous testing of multiple variables within a theoretical framework, assessing the strength and direction of relationships among them [23]. This technique is widely applied across various research disciplines to investigate causal relationships, which are typically linear [24]. While observed variables can be measured directly through surveys or other methods, latent variables such as self-esteem, quality of life, and job satisfaction cannot be directly observed and must be inferred from measurable indicators [24]. The primary objectives of SEM, as identified by [25][26][27], are to explore correlation and covariance patterns among variables and to maximise the explained variance within a given theoretical model. By doing so, SEM helps researchers refine theoretical constructs and validate measurement models. The relationships within SEM are typically represented diagrammatically using standardised notations, as outlined in Table 1 [27]. This visual representation aids in the interpretation of model specifications, allowing for clearer conceptualisation of variable interdependencies and improving the robustness of statistical analyses.

Table 1. SEM Diagram Notations

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 the regression of a latent variable on an observed variable

A composite or full SEM includes a measurement model that defines the relationships between observed variables and their constructs, and a structural model that shows the relationships among constructs. Figure 2 illustrates the basic structure of a composite SEM.

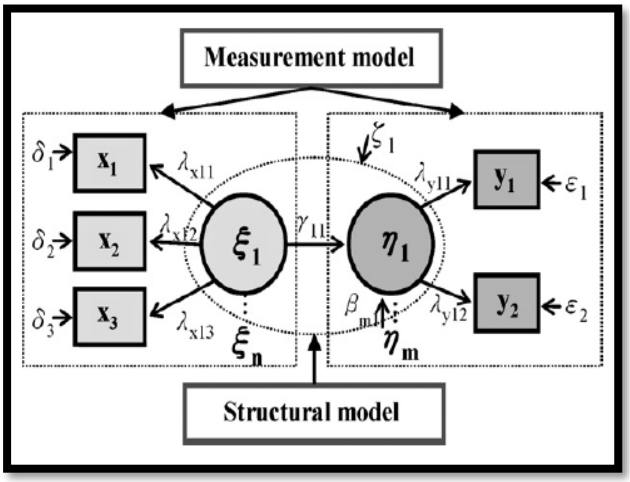


Figure 2: The Basic Structure of a Composite SEM

Where,

$\boldsymbol{X}$ -	Vector of observed exogenous variables
$\boldsymbol{Y}$ -	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 $\boldsymbol{\eta}$ or $\boldsymbol{\xi}$

The measured model and the structural model are respectively given in equations 1 and 2 [30].

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

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

2.4 Statistics of SEM

There are several statistical tests required to determine the adequacy of the 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.

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

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 [29] as an “index to summarise 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 [28].

(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 [28]. 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.

2.5 Artefact to be Evaluated

In this study, the artefact developed for evaluation using TAM was an Android-based mobile application, specifically a customised KMS designed to facilitate the dissemination of knowledge on intelligent rice farming practices. The KMS was meticulously developed to enhance accessibility and usability, incorporating user-friendly information retrieval and advanced search functionalities. The interface was designed to be highly intuitive, featuring a well-structured graphical user interface that allows users to navigate seamlessly through the system. Additionally, the application was equipped with comprehensive security measures, including access control mechanisms, to safeguard data integrity and ensure user privacy. These security features were implemented to mitigate unauthorised access, thereby fostering trust and encouraging widespread adoption among rice farmers.

3. RESULTS AND DISCUSSIONS

3.1 Descriptive Statistics of the Respondents

The evaluation study was conducted among rice farmers in Afere, Western North Region of Ghana, to assess the acceptance of a Knowledge Management System (KMS) designed to support intelligent agricultural practices. As shown in Table 2, a total of 315 farmers voluntarily participated, comprising 79 females (25.08%) and 236 males (74.92%), with the majority (65.71%) aged between 31 and 50 years, indicating active engagement in rice farming. The absence of participants aged 15-20 years suggests limited interest among younger generations, while the low representation of those over 60 years (0.95%) highlights the physically demanding nature of rice farming. In terms of education, only 1.59% of respondents had tertiary-level qualifications, whereas most had completed Junior High School (33.33%) or Senior High School (35.24%), indicating a moderate literacy level. However, 8.89% had no formal education, which may pose challenges in adopting digital tools and technologies.

Table 2. Demographic Attributes of the Respondents

	Frequency	Percentage
Gender		
Male	236	25.08

Female	79	74.92
Age Range		
15-20 years	0	0.00
21-30 years	63	20.00
31-40 years	102	32.38
41-50 years	105	33.33
51-60	42	13.33
Over 60 years	3	0.95
Highest level of Education		
Primary Level	66	20.95
Junior High School	105	33.33
Senior High School	111	35.24
Tertiary	5	1.59
None	28	8.89

3.2 Model Design with SEM to Evaluate the Acceptance of KMS

In line with the hypotheses, the following constructs were formulated to test the level of acceptance of the KMS to support intelligent rice farming. Each construct was measured on a Likert scale ranging from 1 to 5, with the following interpretations:

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

The constructs are given in Table 3.

Table 3. The Constructs for the Study

Construct	
Perceived Usefulness (PU)	
PU1:	Using the KMS in my farming activities would give me the knowledge to accomplish tasks more quickly.
PU2:	Using the KMS would give me the knowledge to improve my farming performance.
PU3:	Using the KMS would give me the knowledge to increase my productivity.
PU4:	Using the KMS would give me the knowledge to enhance my efficiency and accuracy in farming.
PU5:	Using the KMS would give me the knowledge on how to make my work easier.
PU6:	The KMS would be useful in my rice farming.
Perceived Ease of Use (PEOU)	
PEOU1:	Learning to operate the KMS would be easy for me.
PEOU2:	I would find it easy to get the KMS to give me the knowledge to do my work.
PEOU3:	My interaction with the KMS would be clear and understandable.
PEOU4:	I would find the KMS clear and understandable.
PEOU5:	It would be easy for me to master the use of the KMS.
PEOU6:	I would find the KMS easy to use
Attitude Towards Use (ATU)	
ATU1:	I am looking forward to using the KMS 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 the KMS.
Behavioural Intention to Use (BIU)	
BIU1:	I intend to continue using the KMS in the future.
BIU2:	I expect that I will use the KMS in the future.
BIU3:	I plan to use the KMS in the future.
Actual System Usage (ASU)	
ASU1:	I plan to use this system in the future
ASU2:	I currently use this system.
ASU3:	I will continue to use this system.

3.3 Statistical Procedure for the SEM

The collected questionnaire data were systematically processed, beginning with entry into MS Excel, followed by cleaning, coding, and subsequent transfer to SPSS AMOS for analysis. Key variables, including perceived usefulness, attitude, behavioural intention, perceived ease of use, and actual system use, were structured into separate columns. To ensure data integrity, a random 10% sample was inspected for coding accuracy and consistency. Descriptive statistical analyses, utilising SPSS's standard deviation tool, were conducted to assess data quality, identify missing values, and detect potential outliers that could impact the model's validity. SEM was employed in SPSS AMOS to test the study's hypotheses, with the developed model visually represented in Figure 3.

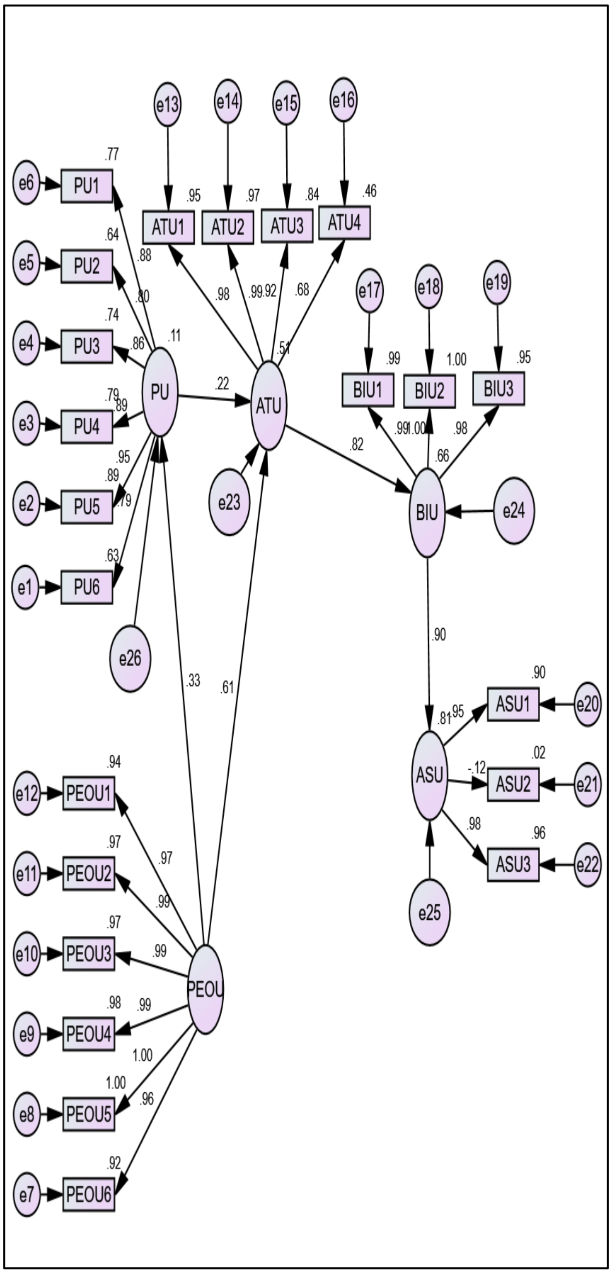


Figure 3: Graphical Representation of the Developed Model

3.4 Model Fit Analysis

The Maximum Likelihood method was employed to estimate the model fit indices, which were subsequently refined to improve overall model fitness. The final model yielded a Chi-square (χ^2) value of 184.778 with a probability of 0.00 and a degree of freedom of 122, indicating a statistically significant model. Several additional model fit indices, as presented in Table 4, were used to evaluate the acceptance of the KMS. These included key assessment criteria such as the Root Mean Square Error of Approximation (RMSEA), Normed Fit Index (NFI), Comparative Fit Index (CFI), and the Ratio of Chi-square to degrees of freedom (X^2/df), all of which collectively demonstrated a strong fit with the data.

The robust model fit indices provide compelling evidence of the model's validity in identifying key parameters that influence rice farmers' acceptance and adoption of the KMS. This suggests that the proposed model effectively captures the factors shaping farmers' behavioural intentions and actual system use. The findings reinforce previous research by [32][33], which similarly confirmed the effectiveness of such models in predicting technology adoption in agriculture. These results underscore the reliability of the developed KMS model as a tool for understanding and enhancing knowledge-sharing practices among rice farmers.

These fit indices indicate that the model provides an excellent fit to the data, as per commonly accepted SEM thresholds [26][34]. A CFI value above 0.95 and an RMSEA below 0.05 suggest that the model aligns well with the observed data, confirming its robustness and validity [35].

Table 4. Model Fit Index

Index	Model Output	Threshold	Observation
CFI	**0 .995**	**>0.90**	**Good fit**
RMSEA	**0.040**	**<0.08**	**Good fit**
NFI	**0.985**	**>0.90**	**Good fit**
X 2/df	**1.51**	**<5**	**Good fit**

3.5 Hypothesis Testing

The hypotheses were tested based on the standardised regression weight estimates given in Table 5 and the effects on each hypothesis path in Table 6 obtained from SEM. The maximum likelihood estimates established that the paths between PEOU→ATU, ATU→BIU and BIU→ASU are very significant, while the paths between PU→ATU and PEOU→PU were moderately significant. Per these observations, hypotheses H2, H4 and H5 are strongly supported, while hypotheses H1 and H3 are moderately supported. All five hypotheses (H1 to H5) were supported, with none being rejected, as shown in Table 5; the only difference is how strongly each hypothesis is supported.

Table 5. Model Estimates Summary

Hypotheses	Hypothesised Path direction	Standardised Estimates	p-value	T-statistic (Critical Ratio)	Result of Hypothesis
H1	PU → ATU	0.116	0.004**	2.915	Significant
H2	ATU → BIU	0.994	0.000***	20.802	Very Significant
H3	PEOU → PU	0.378	0.000***	4.610	Significant

H4	PEOU→ ATU	0.727	0.000***	16.299	Very Significant
H5	BIU → ASU	0.968	0.000***	28.060	Very Significant

***p < 0.005; ***p < 0.001*

Table 6. Path Effects Table

Path	Direct Effect	Indirect Effect	Total Effect
PU → ATU	0.116	0.000	0.116
ATU → BIU	0.994	0.000	0.994
PEOU → PU	0.378	0.000	0.378
PEOU→ ATU	0.727	0.044	0.771
BIU → ASU	0.968	0.000	0.968

3.6 Findings Based on the Evaluation of Rice Farmers' Acceptance of the KMS

The TAM framework was employed to evaluate the acceptance level of a KMS among rice farmers. The TAM constructs were integrated into an SEM approach using the software AMOS to identify the key determinants influencing farmers' acceptance and eventual adoption of the system. The findings from the model align with existing TAM and SEM research works, which theorise that the perceived ease of use of a system significantly affects perceived usefulness and attitudes, ultimately shaping behavioural intentions and actual system usage [4][35][36][38].

Using the standardised estimated findings of the total effects from the SEM results shown in Figure 4, the PEOU of the KMS played a dual and significant role in influencing the ATU and PU of the KMS. The ATU primarily drives BIU, which translates almost directly into ASU. The significant influence of PEOU on both PU and ATU suggests that ease of use is critical for the adoption of the KMS. Therefore, enhancing the system's usability could lead to greater acceptance of the KMS among rice farmers. The highly significant effect of ATU on BIU highlights the importance of shaping positive user attitudes toward the KMS. Training sessions with teaching and learning aids that highlight the benefits of KMS in rice farming could foster more favourable attitudes towards the KMS. The highly significant link between BIU and ASU suggests that strategies aimed at boosting intention, such as incentives, could translate into increased system use.

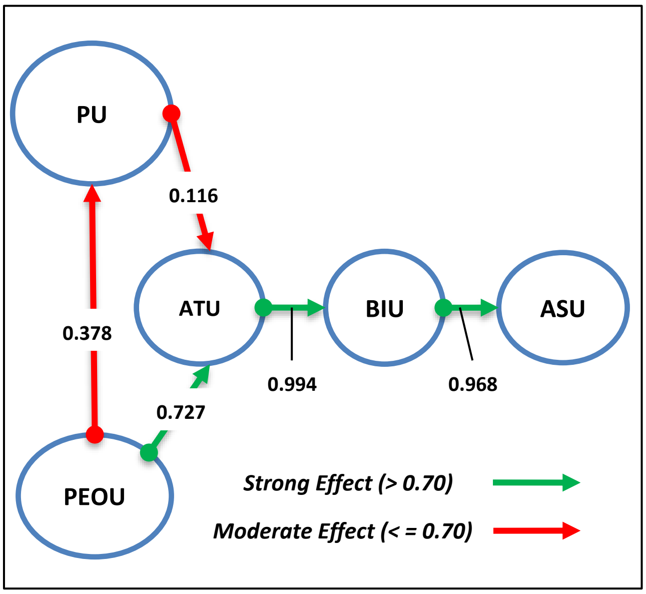


Figure 4: AMOS Parameter estimates of the structural model for the KMS

4. CONCLUSION

This study validates TAM's applicability in evaluating KMS acceptance among rice farmers, demonstrating that perceived ease of use, perceived usefulness, attitudes, and behavioural intentions significantly influence actual system use. The high model fit indices (CFI = 0.995, RMSEA = 0.040) confirm the robustness of the proposed model used.

It is therefore recommended that to enhance the adoption and effectiveness of KMS for rice farmers, it is essential to improve usability by simplifying system navigation and integrating localised language support, thereby enhancing perceived ease of use and user attitudes. Additionally, targeted training programs should be developed to address digital literacy challenges and build user confidence. Positive attitudes toward the system can be fostered through the dissemination of success stories, farmer testimonials, and government-backed awareness campaigns. Furthermore, sustained behavioural intentions and actual system use can be encouraged through incentives such as subsidies and farming grants, reinforcing long-term engagement with the KMS. By implementing these strategies, the KMS can maximise adoption and contribute to improved rice farming efficiency and sustainability in Afere, Ghana.

Future research should adopt a more comprehensive framework for evaluating KMS. While this study focused on perceived ease of use, perceived usefulness, intention to use, and actual usage, it did not account for factors such as social influence and facilitating conditions. Incorporating the Unified Theory of Acceptance and Use of Technology (UTAUT) in subsequent studies is recommended, as it encompasses these additional variables and offers a more holistic understanding of technology adoption.

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