OPEN ACCESS Int. J. Agr. Ext. 12 (03) 2024. 361-378 DOI: 10.33687/ijae.012.003.5340

Check for updates

Available Online at EScience Press
International Journal of Agricultural Extension
ISSN: 2311-6110 (Online), 2311-8547 (Print)
https://esciencepress.net/journals/IJAE

FACTORS INFLUENCING THE BEHAVIOUR OF EXTENSION AGENTS TOWARDS THE ADOPTION OF DIGITAL TECHNOLOGIES IN AGRICULTURAL EXTENSION: A THEORY OF PLANNED BEHAVIOUR PERSPECTIVE

[a]Isaac K. Asante*, [b]Enoch T. K. Ametepey, [c]John K. Ocran, [d]Selorm Omega, [d]Festus Annor-Frempong
[a] Department of Agricultural Science Education, Faculty of Science Education, University of Education, Winneba, Ghana.
[b] Department of Agricultural Education, Communications and Technology, University of Arkansas, United States of America.
[c] Council for Scientific and Industrial Research, Head Office, Accra, Ghana.
[d] Department of Agricultural Economics and Extension, University of Cape Coast, Ghana.

ARTICLE INFO

Article History
Received: August 18, 2024
Revised: November 26, 2024
Accepted: December 02, 2024

Keywords
Adoption behaviour
Agricultural Extension
Extension agents
Digital technologies
Theory of Planned Behaviour
Intention
Behaviour

ABSTRACT

The study examined the agricultural extension agents' behaviour towards adopting digital technologies such as mobile applications and the factors influencing their adoption behaviour. The Theory of Planned Behaviour was used as the theoretical framework to evaluate the adoption intention and behaviour of the extension agents. A descriptive survey design was employed to sample 125 extension agents in four administrative regions in Ghana. Data were collected using a questionnaire and analysed using Statistical Package for Social Sciences (SPSS) v27 and SmartPLS software v 4.0. Frequencies, percentages, means, standard deviations, and partial least squares structural equation modelling (PLS-SEM) were used for data analysis. The results indicated that male (91.2%) extension agents dominate their female counterparts with a mean age of 35.67±7.00 years and 8.06±6.53 years of experience. The results of the PLS-SEM also showed that intention and perceived behavioural control (PBC) predicted 62% of the variations in behaviour. In comparison, attitudes and subjective norms (SN) were determinants of 58% of the intention to adopt digital technologies. Extension agents showed positive intention and behaviour regarding adopting digital technologies in discharging agricultural extension advisory services. However, they perceived the use of these tools as complex or challenging. The results of this study highlight the necessity of customized interventions and capacity building programmes that support extension agents in successfully using digital technology.

Corresponding Author: Isaac K. Asante
Email: ikasante@uew.edu.gh

INTRODUCTION

Globally, technology-driven agriculture is increasingly replacing traditional subsistence farming as nations seek rapid economic growth and embrace new technologies across both developed and developing regions (Ministry of Food and Agriculture-Directorate of Agricultural Extension Services [MoFA-DEAS], 2003; Uzun et al., 2019). The improvement of agricultural yield, efficiency, and sustainability hinges on farmers' readiness to adopt and effectively utilize novel technologies, including digital innovations (Annor-Frempong et al., 2006; Tsan et al., 2019). Agricultural advisory and extension services are critical in ensuring the availability of these technologies and preparing farmers for their adoption

(Dibaba & Biazin, 2022). The role of extension services in facilitating access to improved technologies through appropriate service providers is vital in addressing farmers' needs and concerns, ultimately enhancing agricultural productivity (Danso-Abbeam et al., 2018). By prioritizing technology adoption, effective agricultural extension services are driving transformative changes in agriculture (Ortiz-Crespo et al., 2021). One of the most significant transformations in global agriculture and agri-food systems is digitalization, which involves using digital technologies, innovations, and data to revolutionize business models and practices across the agricultural value chain. This process addresses key bottlenecks such as productivity, post-harvest handling, market access, financing, and supply chain management (Tsan et al., 2019; El Bilali and Allahyari, 2018).

In Sub-Saharan Africa, digitalization is heralded as a "game changer" route to transformation for communities and farmers (Nyarko and Kozári, 2021; Jakku et al., 2022). In particular, digital agricultural tools like artificial intelligence, sensors, robotics, and communication connections are being integrated into agricultural fields, which improves production, profitability, access to information, and resilience for communities and smallholders, as well as response to climate change (Ahsan et al., 2023). This has occasioned a significant rise in the market share of digital agriculture. For example, The Sub-Saharan Africa market for digital agriculture is expected to grow significantly over the next several years from its anticipated value of \$22.0 billion in 2023 to \$36.0 billion in 2028 with a potential Compound Annual Growth Rate (CAGR) of 10.3% (Markets and Markets, 2024).

Existing studies have documented the use of various digital technologies by agricultural extension agents in Ghana. These include GPS mapping for estate management (Bosompem, 2021), the integration of digital tools for communication (Nyarko and Kozári, 2021), and the delivery of extension services through mobile applications, social media, and other innovations (Atengdem et al., 2022). However, research on the effectiveness and sustainability of these digital interventions in addressing key challenges faced by farmers remains limited. Abdulai et al. (2023) highlighted the role of NGOs and private initiatives in supporting digital engagement through SMS, radio, and IVR, yet the extent to which these initiatives align with national agricultural policies and their long-term impact on the quality and accessibility of extension services is underexplored. Similarly, Ocran et al. (2024) emphasized the critical role of extension agents in driving digitalization but noted insufficient understanding of how these agents adapt to and are trained for rapidly evolving digital technologies, particularly in resource-constrained rural settings.

Studies have also explored the expansion of digital agriculture in Ghana. Annor-Frempong and Akaba (2020) investigated the socio-economic impact and acceptance of drone-applied pesticides on maize, finding that farmers' intention to adopt this technology for fall armyworm control was influenced by their attitude toward the technology, perceived enjoyment, demonstrability of results, perceived usefulness, and voluntariness. Omega et al. (2020) noted that while most farmers lacked the financial resources to purchase drone technology due to limited credit accessibility and weak income sources, they were willing to pay for drone services. Their study sought to show the significance of perceived utility and accessibility in shaping attitudes and behaviours toward the adoption of digital technologies. Similarly, extension agents' behaviour toward adopting digital technologies may be influenced by factors such as perceived utility, access to resources, and cost-effectiveness. Ocran et al. (2024) further examined the benefits, barriers, challenges, and requirements for the application of digital technologies among extension agents, revealing that these agents largely value the benefits of deploying such innovations.

Atengdem et al. (2022) argued that Ghana is increasing its digital infrastructure capacity to empower extension agents as leaders of farmer groups, trainers of trainees, problem solvers, and educators in digital agriculture. However, Abdulai et al. (2023) identified challenges such as low literacy rates, lack of digital skills, and limited access to digital resources, which hinder participation in agricultural digitalization. Ahsan et al. (2023) added that inadequate research on the behaviour of extension agents towards digital tools contributes to persistent knowledge gaps. To address these gaps, it is essential to expand the body of knowledge on the utilization of digital technologies in agricultural extension (Ocran et al., 2024).

This study sought to examine the behaviour of extension agents toward adopting digital technologies in agricultural extension in Ghana, along with the factors influencing their adoption. Ajzen's (1991) Theory of Planned Behaviour (TPB) served as the theoretical framework, given its robust application in predicting intentions and behaviours related to technology and services. TPB also facilitates the exploration of additional conceptual factors (Rezaei et al., 2019; Ghali-zinoubi, 2022). In applying TPB, this study aimed to assess the intentions and behaviours of extension agents in adopting digital technologies for extension services. The findings of this study hold practical and policy significance. They can help extension agents evaluate their needs, attitudes, and skills to leverage improved digital infrastructure for effective service delivery. Moreover, the results provide policymakers with critical information to design tailored capacity-building initiatives, fostering full-scale digitalization in agricultural extension in Ghana. The specific objectives of the study were to examine:

1. the behaviour of extension agents towards the adoption of digital technologies in agricultural extension,
2. the intention of extension agents to adopt digital technologies in agricultural extension,
3. attitude of extension agents towards digital agricultural extension delivery,
4. subjective norms influencing the decision of extension agents to adopt digital technologies in agricultural extension,
5. extension agents' behavioural control in applying digital technologies in agricultural extension.

Theoretical framework

Several theories have been utilised to predict technology behaviour towards a new technology (Lai, 2017), including the Diffusion of Innovation Theory (Rogers, 2003), the Theory of Reasoned Action (Fishbein and Ajzen, 1975), the Theory of Planned Behaviour (Ajzen, 1991), and the Technology Acceptance Model TAM 1, 2 and 3 (Davis, 1989; Venkatesh and Davis, 2000; Venkatesh and Bala, 2008). This present study adopted Ajzen (1991) Theory of Planned Behaviour due to its utility and flexibility for investigating psychological constructs underpinning technology adoption behaviour and intention of actors in the field of agriculture (Bagheri et al., 2021; Gholamrezai et al., 2021; Asante et al., 2023) and other fields of study (Chen and Kuo, 2022; Rajeh, 2022; Shirahada & Zhang, 2022). Furthermore, TPB was used in this study to examine and clarify the behaviour of agricultural extension agents towards adopting digital technologies in agricultural extension in Ghana (Dong et al., 2022; Lee et al., 2023). TPB was useful in this study because the theory is a key socio-cognitive model for determining the intention and behaviour toward technology adoption in agriculture (Karapandzin et al., 2019; Asante et al., 2023).

The theory states that behaviour is the outcome of behavioural intention, which is impacted by attitudes towards the behaviour, subjective norms, and perceived behavioural control (Ajzen, 1991). TPB is premised on the notion that the behaviour of a person is the result of a series of factors (Fishbein and Ajzen, 2010; Moon et al., 2019), including intention, which signifies a person's readiness or willingness to engage in a particular behaviour (Gholamrezai et al., 2021). Implying that if someone has a strong intention towards a behaviour, they are likelier to carry out that behaviour (Daxini et al., 2019; Rajeh, 2022). According to Ajzen (1991), intention is determined by three socio-psychological factors: attitudes, subjective norms, and perceived behavioural control. A positive or negative evaluation of engaging in a specific behaviour is denoted as attitude (Aliabadi et al., 2020). Subjective norm is the degree to which an individual feels pressured by significant others to participate in or abstain from a particular behaviour (Shirahada and Zhang, 2022). Because people fear rejection, they often adhere to arbitrary principles and standards (Rajeh, 2022). Perceived behavioural control (PBC) refers to an individual's belief in their capacity to carry out a specific behaviour (Gholamrezai et al., 2021).

In this study, the Theory of Planned Behaviour (TPB) holds that attitude reflects the agents' evaluation of the benefits of digital tools, such as improved efficiency and service delivery, with positive attitudes likely increasing adoption intentions. Subjective norms highlight the influence of social pressures from peers, supervisors, and farmers, where supportive norms strengthen the intention to adopt. Perceived behavioural control captures agents' confidence in their ability to use these tools, considering factors like access to resources and skills, which directly impact both intention and behaviour. Intention, shaped by these constructs, mediates the link to actual adoption, while higher perceived control can directly enable behaviour. TPB is ideal for this study as it integrates cognitive, social, and resource-related dimensions, offering a comprehensive and predictive approach to understanding extension agents' adoption of digital technologies.

Like every theory, some scholars have raised concerns about TPB not providing precise direction on change procedures (McEachan et al., 2011), its validity and utility (Sniehotta et al., 2014) and predictive power of the theory (Fishbein and Ajzen, 2010). Despite these critiques, TPB has been widely applied in different fields and more specifically in the field of agriculture to examine the intention and behaviour of actors in appropriate pesticide use behaviour (Bagheri et al., 2021; Loha et al., 2022; Asante et al., 2023), students' intention to participate in a career in agriculture (Zaremohzzabieh et al., 2022; Hur et al., 2024), intention of rural people to adopt sustainable water management by rainwater harvesting (Gholamrezai et al., 2021), understanding forest land conservation for agriculture (Ibrahim et al., 2022), intention of farmers to adopt integrated pest management practices (Karapandzin et al., 2019; Asante et al., 2023), and intention of farmers to renew productive agricultural contracts (Xu et al., 2022).

In short, Ajzen (1991) states in TPB that an individual's motivation and intention to engage in a given behaviour will increase with how ideal their attitudes towards that behaviour are, as well as how much social norms and perceived behavioural control there are around that behaviour (Carfora et al., 2019; Daxini et al., 2019; Shirahada and Zhang, 2022; Zaremohzzabieh et al., 2022). This present study adopted TPB to examine the intention and behaviour of agricultural extension agents towards applying digital technologies in agricultural extension. The study also examined the composite effect of attitude, subjective norm and perceived behavioural control on intention and behaviour. In doing so, the following hypotheses were formulated:

$H_0$1: Agricultural extension agents' intention significantly influences their behaviour towards applying digital technologies in agricultural extension.

$H_0$2: Agricultural extension agents' perceived behavioural control significantly affects their behaviour towards digital technologies in agricultural extension.

$H_0$3: Agricultural extension agents' attitude significantly influences their intention to use digital technologies in agricultural extension.

$H_0$4: Agricultural extension agents' perceived behavioural control affects their intention to adopt digital technologies in agricultural extension.

$H_0$5: Agricultural extension agents' subjective norms directly influence their intention to adopt digital technologies in agricultural extension.

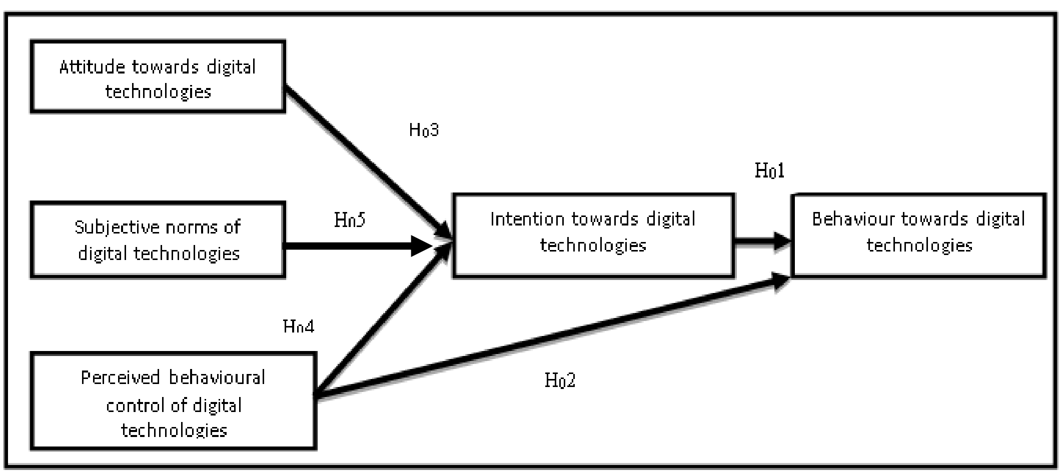

Figure 1. TPB Model of behaviour of agricultural extension agents towards adopting digital technologies in agricultural extension.

METHODOLOGY

A descriptive survey design was used for the study. Descriptive survey design was used to enable agricultural extension agents provide quantitative information about their intention and behaviour towards applying digital technologies in agricultural extension in the operational areas without manipulating the setting (Hall, 2011). Survey design enabled the gathering of information from extension agents at one particular moment regarding the use of digital technologies in agricultural extension (Prince and Das-Munshi, 2020). The study was conducted in four administrative regions in Ghana—Ahafo, Bono East, Central, and Upper East regions with a population of 496 agricultural extension agents (MoFA-DAES, 2021). The four regions were randomly selected from the sixteen regions (Ministry of Local Government and Rural Development, 2023). The study employed a four-stage multi-stage sampling strategy to choose participants (VanderStoep and Johnston, 2009). In the first stage, the nation was divided into four strata. One region was chosen at random from each of the four strata in the second stage. At this point, the regions of Ahafo, Central, Bono East, and Upper East were chosen at random. There were 496 extension agents in these four regions, which corresponded to the study population (MoFA-DAES, 2021). Four districts from each of the four regions were chosen at random for the third stage of the sampling procedure. Four districts were chosen from each region due to the disproportionate number of districts in each region. To represent the fourth stage of the sampling process, respondents for the study were chosen at random from the accessible population of 496 extension agents. The sample size for the study was established by using the table developed by Krejcie and Morgan (1970) to determine the right sample size from a given population. According to the table, approximately 224 extension agents would be a suitable sample size for the population of 496 extension agents. Following the compilation of a list of the extension agents, 14 respondents were randomly selected from each of the 16 districts from the four regions to yield a sample size of 224 extension agents who were selected using the lottery method.

A questionnaire was used as the instrument with two sections. Part one focused on data regarding the extension agents' sociodemographic characteristics whereas data on the TPB constructs were collected using Part two. The TPB constructs used in the study were adopted from Fishbein and Ajzen (2010). The TPB variables were adjusted to better fit the study's objectives. Attitudes, perceived behavioural control and subjective norm had six indicators, whiles behaviour and intention had five items each (Bishop and Herron, 2019). The face and content validity of the questionnaire were evaluated by two specialists in agricultural extension from the Department of Agricultural Science Education at the University of Education, Winneba. The experts offered their advice to guarantee that the questionnaire items accurately measured the study's objectives (Memon et al., 2023). To assess the questionnaires' reliability, pre-testing was done using ten extension agents in the Greater Accra Region (Vonglao, 2017). McDonald's Omega coefficients of the Likert type sub-scales were computed using data from the pre-testing exercise with International Business Machine Statistical Package for Social Sciences (IBM SPSS) version 27 (Şimşek and Noyan, 2013). McDonald's Omega coefficients of the TPB pre-tested data were perceived behavioural control (0.88), behaviour (0.94), intention (0.95), subjective norm (0.96), and attitudes (0.98). The results show that the items on the questionnaire had lower standard error, and thus demonstrated higher reliability (Hayes and Coutts, 2020). Before data collection, ethical clearance was obtained from the Ethical Review Board of the University of Education, Winneba. The questionnaires were then administered to the extension agents through a self-administration process for a period of one month (April 1-30th 2024). One hundred and twenty-five (n = 125) extension agents returned the questionnaires at the end of April 2024.

The study utilized descriptive statistics (frequency, percentages, means and standard deviation) with IBM SPSS version 27 and Partial Least Squares Structural Equation Modelling (PLS-SEM) with Smart PLS version 4 to analyse the data (Ringle et al., 2022). PLS-SEM was used to estimate the outer and inner models of the TPB constructs (Shiau et al., 2019). The analysis of the outer model focused on the validity and reliability of the TPB model. Average variance extracted (AVE) values greater than 0.5 were used to assess the validity of the TPB constructs while composite reliability indices higher than 0.7 were used to examine the reliability of the constructs (Hair et al., 2021). Furthermore, the significance of the inner model was estimated with a coefficient of determination and beta coefficients. T-statistics indices greater than 1.96 and a corresponding alpha level of 0.05, was considered adequate to accept the hypothesis (Sarstedt et al., 2021).

RESULTS

Sociodemographic profile of Extension Agents

Table 1 presents the socio-demographic characteristics of the extension agents. Around 91.2% of extension agents are males with a mean age of 35.67±7.00 years. Six out of every ten extension agents are between 31 and 40 years old, with one-fifth (20.0%) being less than 31 years old. Of the total extension agents, 76.8% had working experience between 1 and 10 years, with mean experience of 8.06±6.53 years. And 84.8% of the extension agents were working in rural communities. A little over three-fourths (77.6%) of the extension agents were married, with more than half (52.8%) holders of bachelor's degrees in various agricultural fields. A certificate in agriculture is the minimum qualification needed to work in extension in Ghana, though certificate holders are in the minority. Extension agents specialised in General Agriculture (60.8%) dominate the areas of specialisation. This is followed by those specialising in Agricultural Extension (14.4%). Around 61% of extension agents have received some form of training in applying digital technologies in agriculture.

Table 1. Sociodemographic characteristics of extension agents.

Variables	Frequency	Percent
Sex of extension agents		
Male	114	91.2
Female	11	8.8
Age (years) [$\bar{X}$ = 35.67±7.00]		
Up to 30	25	20.0
31 – 40	76	60.8
41 – 50	16	12.8
51 – 60	8	6.4
Experience (years) [$\bar{X}$ = 8.06±6.53]		
1 – 10	96	76.8
11 – 20	22	17.6
21 – 30	7	5.6
Location of operational area		
Rural	106	84.8
Urban	19	15.2
Marital status		
Married	97	77.6
Single	26	20.8
Divorced	1	0.8
Widow	1	0.8
Level of education		
Certificate level	22	17.6
Diploma level	21	16.8
Bachelor degree level	66	52.8
Master's degree Level	16	12.8
Area of specialization		
General Agriculture	76	60.8
Agricultural extension	18	14.4
Crop science	8	6.4
Post-harvest	7	5.6
Agricultural engineering	6	4.8
Animal health (Veterinary)	5	4.0
Animal science	4	3.2
Horticulture	1	0.8
Received training in digital technologies		
Yes	76	60.8
No	49	39.2

Factors influencing the behaviour of Extension Agents towards the adoption of digital technologies in agricultural extension

Table 2 presents the TPB factors extension agents' behaviour towards adopting digital technologies in agricultural extension in Ghana. The variable that scored highest among the TPB constructs was attitudes towards the adoption of digital technologies in agricultural extension with an overall mean of 3.88±1.14. On the other hand, perceived behavioural control of the extension agents was assessed with the lowest overall mean of 2.93±0.97. Largely, the extension agents showed 'high' positive attitude concerning the adoption of digital technologies in agricultural extension. The extension agents noted that application of digital technologies is important and beneficial for extension delivery. Behaviour toward application of digital technologies for agricultural extension had the second highest overall mean among the TPB constructs with an overall mean of 3.79±1.11. The results showed that extension agents showed high behaviour towards using and promoting digital technologies for extension delivery.

Intention towards digital technologies for agricultural extension scored the third highest with an overall mean of 3.60±1.15. Extension agents showed high intention because they are expected to adopt digital technologies for extension activities with farmers and enhance extension output in the foreseeable future. The TPB construct, subjective norm, scored the fourth highest mean with an overall mean of 3.21±1.11, indicating that extension agents perceive the influence of important associates on their intention to adopt digital technologies for agricultural extension delivery to be moderately high. The results suggest that the influence of people whose opinions extension agents value, respect and admire, including family and friends, relating to their intention to adopt digital technologies in agricultural extension is moderately high. Perceived behavioural control showed the lowest mean with an overall mean of 2.93±0.97. Extension agents indicated that they possess sufficient self-confidence and control to make decisions to adopt digital technologies for extension delivery in Ghana. Extension agents also indicated that they possess moderately high knowledge towards using digital technologies for extension delivery.

Table 2. Factors influencing the behaviour of AEAs towards the adoption of digital technologies in agriculture extension

Statement	Mean	S.D
Behaviour		
I engage in the use digital technologies for extension delivery	3.98	1.19
I conduct extension delivery services with digital technologies	3.78	1.18
I promote the use digital technologies for extension delivery	3.77	1.28
I encourage the use digital technologies for extension delivery	3.75	1.25
I appreciate the use digital technologies for extension delivery	3.69	1.27
Overall mean	*3.79*	*1.11*
Intention		
I intend to adopt digital technologies for my extension activities with farmers	3.66	1.26
I plan to use digital technologies to enhance my work output	3.66	1.21
I intend to use digital technologies for extension delivery in the near future	3.65	1.27
I plan to use digital technologies for extension delivery in the near future	3.55	1.27
I predict I would use digital technologies in the near future	3.47	1.29
Overall mean	*3.60*	*1.15*
Attitudes		
Application of digital technologies are important for improving extension delivery	3.92	1.23
Application of digital technologies is beneficial in agricultural extension delivery	3.91	1.17
Digital technologies are useful in agricultural extension delivery	3.89	1.12
Digital technologies make agricultural extension delivery productive	3.88	1.24
Application of digital technologies in agricultural extension is good	3.86	1.26
Digital technologies are valuable in agricultural extension delivery	3.81	1.22
Overall mean	*3.88*	*1.14*
Subject norms		
Most people whose opinions I value think that it is good to use digital technologies for extension delivery	3.31	1.19
Most people whom I respect would like me to use digital technologies for extension delivery	3.30	1.28
Most people whom I admire would like me to use digital technologies for extension delivery	3.26	1.19
My close family think I should use digital technologies for extension delivery	3.20	1.31
Most people who are important to me want me to use digital technologies for extension delivery	3.11	1.20
Most people who are important to me think I should use digital technologies for extension	3.04	1.22

delivery		
Overall mean	*3.21*	*1.11*
Perceived behavioural control		
I have sufficient self-confidence to make the decision to adopt digital technologies for extension delivery	3.31	1.21
I have sufficient control to make the decision to adopt digital technologies for extension delivery	2.98	1.25
If I really wanted to I could use digital technologies for extension delivery in the next few months	2.90	1.21
I have complete control over using I have complete control	2.81	1.28
I have sufficient knowledge to use digital technologies for extension delivery	2.80	1.19
My using digital technologies for extension delivery is completely up to me	2.76	1.21
Overall mean	*2.93*	*0.97*

Means were computed on a scale of 1 = Very low agreement, 2 = low agreement, 3 = moderate agreement, 4 = high agreement, 5 = very high agreement

Evaluation of the TPB measurement model

Table 3 presents PLS-SEM results of the measurement model of the TPB constructs used in the study. The measurement model evaluated the TPB constructs' reliability, convergent, and discriminant validity. The factor loadings, Cronbach's alpha, Joreskog's rho A (calculated using the unstandardised loadings), and composite reliability (computed using the standardised loadings) (Hair et al., 2017).

Evaluation of the factor loadings of the TPB constructs revealed that all constructs had factor loadings greater than the threshold of 0.70, endorssing reliability (Hulland, 1999; Hair et al., 2011). The Joreskog's rho A, composite reliability and Cronbach's alpha of the TPB constructs recorded values greater than 0.70, demonstrating indicator reliability (Nunnally, 1978) and internal consistency (Gefen et al., 2000). The average variance extracted (AVE) function was used to examine the convergent validity of the TPB constructs used in the study. The TPB constructs showed adequate convergent validity with values greater than the threshold of 0.50 (Bagozzi et al., 1991). The discriminant validity of the TPB constructs was examined using the heterotrait-monotrait (HTMT) ratio criteria proposed by Henseler et al. (2015). The HTMT is the mean value of the construct indicator correlation across constructs relative to the (geometric) mean of the average correlation for the indicators measuring the same construct (Hair et al., 2019). The TPB constructs used in the model achieved discriminant validity based on the HTMT ratios with all indices less than the recommended threshold of 0.85 for all variables in the model (Hair et al., 2021).

Table 3. Factor loadings, reliability, and convergent criteria.

Item	Loading	Cronbach's Alpha	ρA	ρC	AVE
Attitudes (ATT)					
ATT1	0.92	0.98	0.98	0.98	0.89
ATT2	0.95				
ATT3	0.95				
ATT4	0.96				
ATT5	0.94				
ATT6	0.96				
Behaviour (BEH)					
BEH1	0.84	0.94	0.94	0.95	0.81
BEH2	0.93				
BEH3	0.92				
BEH4	0.92				
BEH5	0.88				
Intention (INT)					
INT1	0.93	0.95	0.96	0.96	0.84
INT2	0.91				
INT3	0.87				
INT4	0.94				

INT5	0.93				
Perceived behavioural control (PBC)					
PBC1	0.74	0.88	0.89	0.91	0.63
PBC2	0.81				
PBC3	0.84				
PBC4	0.72				
PBC5	0.81				
PBC6	0.83				
Subjective norm (SN)					
SN1	0.90	0.96	0.96	0.975	0.82
SN2	0.904				
SN3	0.89				
SN4	0.94				
SN5	0.92				
SN6	0.88				

ATT: attitude; BEH: behaviour; INT: intention; PBC: perceived behavioural control, SN: subjective norms

Table 4, Discriminant Validity based on HTMT Criteria.

Constructs	ATT	BEH	INT	PBC	SN
ATT					
BEH	0.78				
INT	0.75	0.79			
PBC	0.50	0.61	0.50		
SN	0.77	0.70	0.71	0.66	

ATT: attitude; BEH: behaviour; INT: intention; PBC: perceived behavioural control, SN: subjective norms

Evaluation of the TPB structural model

Table 5 presents the structural model indices of the TPB constructs used in the study. Before evaluating the TPB structural model, collinearity diagnostic test was performed to confirm the absence of multi-collinearity in the model. The results of the collinearity diagnostic test showed that TPB constructs recorded variance inflation factors (VIF) less than the accepted threshold of 3.0 which is consistent with the recommendations of Hair et al. (2019) that VIF values should be less or equal to three. Therefore, multi-collinearity did not inflate TPB constructs (Hair et al., 2021). The next structural model indices that was evaluated is the R^2 of the endogenous constructs were intention and behaviour of extension agents towards adoption of digital technologies in agricultural extension. The R^2 of the TPB model were evaluated to determine the variance in the endogenous constructs (intention and behaviour) explained by their respective exogenous constructs (Shmueli and Koppius, 2011). According to Hair et al. (2017), values of that approximately 0.75, 0.50 and 0.25 represent substantial, moderate and weak respectively. The R^2 value of the intention of extension agents' decision to adopt digital technologies in agricultural extension is 0.58, signifying that intention of extension agents was moderately predicted by attitudes, perceived behavioural control and subjective norms. The three exogenous constructs accounts for 58% (R^2: INT = 0.58) of the variance in intention of extension agents' decision to adopt digital technologies for agricultural extension. In addition, the R^2 value of behaviour of extension agents towards application of digital technologies in agricultural extension is 0.62, indicating that two exogenous constructs, intention and perceived behavioural control, close to substantially accounted for 62% (R^2: BEH = 0.62) of the variance in behaviour of extension agents towards application of digital technologies in agricultural extension. The R^2 values of the endogenous constructs show that the TPB model had between moderate and substantial predictive power, hence, is important for explaining the intention and behaviour of extension agents towards application of digital technologies in Ghana. Adopting Cohen's (1988) effect size criteria, the f^2 effect size of the TPB model was evaluated to determine the changes in the R^2 values of intention and behaviour when the respective exogenous constructs were held constant (Hair et al., 2019). Cohen (1988) posited that effect size values greater than 0.02, 0.15, and 0.35, signify small, medium and large effects. The PLS-SEM results show that attitude had medium effect (f^2: ATT = 0.26) on extension agents' intention to adopt digital technologies for agricultural extension. On the other hand, subjective norms had small effect (f^2: SN = 0.05) while perceived behavioural control had no effect on intention of extension agents (f^2: PBC = 0.01) extension delivery. The results also show that intention had very large effect (f^2: INT = 0.75), while perceived behavioural control had medium effect (f^2: PBC = 0.15) on behaviour of extension agents to adopt digital technologies for agricultural extension delivery in the study area.

Stone-Geisser's Q^2 values were computed to examine the predictive accuracy of intention and behaviour of extension agents towards adoption of digital technologies for agricultural extension (Geisser, 1974; Stone, 1974). Using the blindfolding procedure for specific omission distance D, Q^2 were obtained for the TPB model (Hair et al., 2019). Outcomes of Q^2 values greater than zero, 0.25 and 0.50, represent small, medium, and large predictive relevance of the TPB model (Hair et al., 2021). The PLS-SEM results (Q^2: INT= 0.47) and (Q^2: BEH = 0.49) show that attitudes, perceived behavioural control and subjective norms, and intention and perceived behavioural control had moderate predictive relevance with their respective endogenous variables. The results indicate at the TPB model estimation data demonstrated good statistical significance and accuracy of behaviour of extension agents to adopt digital technologies for extension delivery (Sarstedt et al., 2020).

Table 5. TPB Structural model indices.

Relationships	Std. Beta	T-value	P-values	95% BCa confidence interval LB	95% BCa confidence interval UB	VIF	R^2	f^2	Q^2
INT -> BEH	0.61	7.36	0.00	0.44	0.77	1.30	0.62	0.75	0.49
PBC -> BEH	0.27	3.40	0.00	0.11	0.43	1.30		0.15	
ATT -> INT	0.50	5.63	0.00	0.33	0.68	2.27	0.58	0.26	0.47
PBC -> INT	0.08	1.01	0.31	-0.09	0.21	1.66		0.01	
SN -> INT	0.25	2.10	0.04	0.00	0.48	2.85		0.05	

ATT: attitude; BEH: behaviour; INT: intention; PBC: perceived behavioural control, SN: subjective norms; VIF: variance inflation factor; R^2: coefficient of determination; f^2: effect size; Q^2: predictive relevance

Direct relationships and beta coefficients

Utilizing the bootstrapping procedure, the statistical significance of the TPB model from the study sample of 125 was evaluated (Hair et al., 2019). Engaging the bootstrap procedure in PLS-SEM with 5000 samples at 95% confidence interval, beta coefficients and t-statistics were computed (Table 5). The results of the beta coefficient show that, intention and perceived behavioural control had positive significant effect on behaviour of extension agents to adopt digital technologies in agricultural extension. The positive direct effect significance between intention, and perceived behavioural control (INT->BEH: β = 0.61, p = 0.00; PBC -> BEH: β = 0.27, p = 0.00) and behaviour indicated that extension agents have strong intention towards adopting digital technologies for agricultural extension delivery. Also, the strong belief in their capabilities to use novel technologies had a strong influence on their behaviour towards adopting these technologies for extension delivery. The relationships seen between intention and perceived behavioural control, and behaviour showed that the TPB model used in the study supported hypotheses 1 and 2.

The results also show that attitude and subjective norms had positive significant effect on intention of extension agents towards adopting digital technologies for extension delivery. The positive significant relationships between attitude (ATT -> INT: β = 0.50, p = 0.00) and intention denote extension agents have positive attitudes towards adopting digital technologies, which strongly influences their intention to adopt the novel technologies for agricultural extension delivery. In addition, the positive significant relationship between subjective norms (SN -> INT: β = 0.25, p = 0.04) and intention indicates that important family members, friends and close associates are of the opinion that extension agents should adopt digital technologies for extension delivery as it has a noticeable effect on their intention to adopt digital technologies for extension delivery. The positive relationships between attitude, subjective norms, and intention indicate that the TPB model supports hypotheses 3 and 5. On the contrary, perceived behavioural control showed no significant effect (PBC -> INT: β = 0.08, p = 0.31) on intention. This indicates that the extension agents do not have considerable belief in their abilities with the use of digital technologies to control their intention towards adopting digital technologies for agricultural extension. Hypothesis 4, therefore, is not supported by the TPB model used in the study.

PLS predict assessment of manifest variables

To examine the TPB model's out-of-sample prediction power, Shmueli's et al. (2016) PLS-predict techniques was used. In this process, the model's analysis sample (training sample) and its prediction accuracy were evaluated on the data that is not the analysis sample (holdout sample). Table 6 demonstrates that every indicator surpassed the most naïve benchmark (the indicator averages of the training sample) with Q^2 predict values greater than zero (Shmueli et al., 2019). The root mean squared error (RMSE) was used to assess the TPB model's out-of-sample prediction performance; thus, the predictive error did not reveal the distribution to be highly non-symmetrical (Hair et al., 2021).

When the RMSE results from the PLS-SEM were compared with the naïve linear regression model (LM) standard, the PLS-SEM approach produced reduced predicted errors for all the indicators BEH1. For every endogenous construct indicator, there are increasingly noticeable differences between PLS-SEM RMSE and LM RMSE. Because all but one (BEH1 = 0.09) of the PLS-SEM procedure indicators produced prediction errors greater than the naïve LM benchmark, the TPB model employed for the study thus showed moderate predictive power (Sarstedt et al., 2021).

Table 6. PLS predict assessment of manifest variables.

Items	PLS-SEM		LM	PLS-SEM –
	RMSE	Q^2predict	RMSE	LM RMSE
BEH1	0.88	0.46	0.79	0.09
BEH2	0.97	0.43	0.99	-0.02
BEH3	0.86	0.48	0.95	-0.09
BEH4	0.93	0.45	1.05	-0.12
BEH5	0.98	0.41	1.02	-0.04
INT1	0.89	0.51	1.01	-0.12
INT2	0.98	0.42	1.09	-0.11
INT3	1.10	0.28	1.17	-0.07
INT4	0.82	0.54	0.88	-0.06
INT5	0.85	0.54	0.91	-0.06

BEH: behaviour; INT: intention; RMSE: root mean squared error; LM: linear regression model

DISCUSSION

This study sought to examine agricultural extension agents' behaviour towards adopting digital technologies in agricultural extension utilizing Ajzen's (1991) Theory of Planned Behaviour. The Theory of Planned Behaviour (TPB) has been widely applied to understand the behaviour and intentions of agricultural actors (Aliabadi et al., 2020; Gholamrezai et al., 2021; Govindharaj et al., 2021; Zaremohzzabieh et al., 2022; Lee et al., 2023; Asante et al., 2023), demonstrating its effectiveness in predicting the adoption of digital technologies in agricultural extension. This study affirms TPB's relevance for analysing extension agents' decisions to adopt such technologies, as it remains the dominant framework for explaining adoption behaviours in the agricultural sector (Fishbein and Ajzen, 2010). Despite its utility, limited research addresses the behaviour of extension agents toward digital technology adoption in developing countries like Ghana (Ahsan et al., 2023). By providing unique empirical data, this study bridges that gap and highlights the importance of leveraging digital infrastructure initiatives by the Ghanaian government to enhance extension service delivery (Atengdem et al., 2022).

Both intention and perceived behavioural control jointly accounted for approximately 62% of the variance in behaviour of extension agents towards adopting digital technologies in agricultural extension with intention towards adoption of digital technologies exerting the strongest significant effect on behaviour. Significant effect of both intention and perceived behavioural control indicate that when extension agents possess strong readiness to engage in a behaviour of deploying digital technologies in agricultural extension, and have control over performing the behaviour, their behaviour towards adopting the novel technologies for agricultural extension improves (Fishbein and Ajzen, 2010). Both results are similar to the finding of Carfora et al. (2019) which reported a significant effect of intention and perceived behavioural control on behaviour of farmers. Asante et al., (2023) also found out that both perceived behavioural control and intention predict behaviour of farmers towards safe use of pesticides. Our results also confirm that intention is the strongest determinant of behaviour (Gholamrezai et al., 2021; Asante et al., 2023).

Our results on the strong effect of intention on behaviour indicate that extension agents deliberated on and made a conscious decision (create an intention) to conduct or not to conduct extension delivery with novel technologies like digital technologies (Fishbein and Ajzen, 2010). However, as performance opportunities were repeated, the intention was triggered spontaneously, negating the need for deliberation before behaviour (Lai, 2017). Bagheri et al. (2021) studied farmers' behaviour concerning safe pesticide usage and revealed that perceived behavioural control significantly predicted behaviour while intention did not, which contradicts the findings of this study. Wastutiningsih and Aulia (2023) studied food waste behaviour and reported that perceived behavioural control did not significantly impact on households' food waste behaviour. Gholamrezai et al. (2021) posited that a person's behaviour is determined by their ethical obligations, perceptions of and awareness of the effects and the necessity of observing the behaviour to prevent side effects. This suggests that even when people follow social norms, they are the only ones who look for actions that make them feel at ease on the inside, align with their personal ideals, and make them feel like self-sufficient, independent people (Yuriev et al., 2020). The behaviour exhibited due to personal convictions gives the individual a greater sense of freedom and inner fulfilment (Baydur et al., 2023). Our findings infer that agricultural extension agents are highly ready to adopt digital technologies for extension delivery since they have moderate mastery over adopting them (Fishbein and Ajzen, 2010). Attitudes towards digital technologies, subjective norms and perceived behavioural control collectively predicted 58% of the variance in agricultural extension agents' intention to deploy digital technologies for agricultural extension. Of the three predictors of intention, subjective norm and attitude showed significant effect while perceived behavioural control did not. The results indicate that, when extension agents develop favourable attitudes towards novel technologies, and significant influencers like family, friends, colleagues and superiors think that they can utilise digital technologies in extension delivery, their intention to adopt these technologies significantly improves. Attitude was the strongest significant precursor of intention. This suggest that when attitudes of extension agents significantly improve, the consequences are the significant improvement in their readiness to deploy digital technologies for extension delivery. In this respect, previous studies including Bagheri et al. (2021), Damalas (2021), Rajeh (2022), Shirahada and Zhang (2022), and Asante et al. (2023) reported that attitude is the strongest predictor of intention. The results however contradict the finding of Wastutiningsih and Aulia (2023) which reported that the intention of young consumers in Yogyakarta to perform waste food reduction behaviour was not significantly influenced by attitude toward reducing waste food.

The model of this present study showed that subjective norm was a significant contributor to extension agents' intention. Therefore, social pressure or influence brought to bear on extension agents significantly affects their intention to utilise digital technologies. Similar findings were reported by Carfora et al. (2019), Damalas (2021), Govindharaj et al. (2021), and Rajeh (2022) regarding significant impact of subjective norm on intention. Other previous studies have reported contrary to our findings about non-significant effect of subjective norm on intention in different contexts (Rezaei et al., 2019; Shirahada and Zhang, 2022; Asante et al., 2023). The positive effect of subjective norms on intention indicates that social pressure from extension agents' family, friends, colleagues and superiors plays an important role in their readiness to adopt digital technologies in agricultural extension. The role of perceived behavioural control on intention was not significant. This suggests that extension agents perceived the use of digital technologies as difficult and did not influence their intention. The basic idea behind their perception of using digital technologies being difficult is their lack of knowledge and skills in utilising these modern devices (Tian et al., 2023). Our results contradict the findings of prior research, which found a positive effect of perceived behavioural control on intention (Aliabadi et al., 2020; Gholamrezai et al., 2021; Lee et al., 2023). The current study's positive effect of attitude and subjective norm on intention indicates that agricultural extension agents feel more confident about their internal desires and encouragement from family, friends, colleagues and superiors (Quintal et al., 2010). Depending on the behaviour in question, people may be more motivated by subjective norms or by their attitudes (Ibrahim et al., 2022). Therefore, extension agents are driven more by their internal convictions and the following of influential people in society.

This study advances our knowledge of how agricultural extension agents adopt new technologies and emphasises the value of enabling extension workers to act as change agents in the digital era. Our results point to the fact that extension agents have positive intentions and behaviour towards using digital tools, but they perceive using these new devices as difficult. This finding suggests that tailored intervention or training programmes are needed to build the capacity of agents to use these devices effectively. Decision makers can take advantage of the opportunity provided by the positive attitudes and social factors influencing extension agents' intention and, by far, their behaviours when planning such interferons or training programmes. It is important to consider the study's limitations when evaluating the findings. Our reliance on the self-reported opinions of extension agents collected at one point may restrict the findings' generalizability. Increased exposure to digital tools and devices may cause beliefs to shift over time. The study's limited scope, which included extension agents in four of Ghana's sixteen regions, limits the findings' applicability to extension agents throughout the country. Subsequent studies may consider broadening the focus to include the remaining regions in the country.

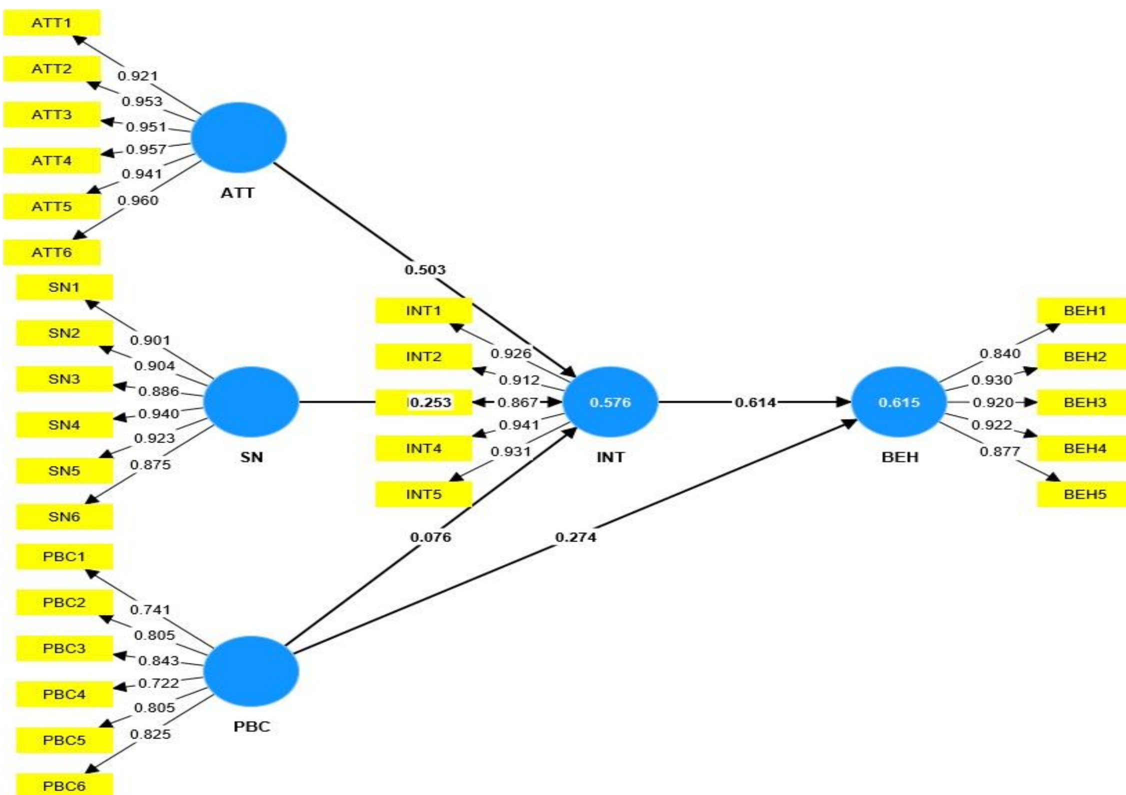

Figure 1. TPB Model of agricultural extension agents' behaviour towards adoption digital technologies for extension delivery.

CONCLUSION

The results of this study highlight how important it is to understand how agricultural extension agents behave when it comes to using digital technologies for agricultural extension work. Digital tools are now essential for improving agricultural productivity, sustainability and livelihoods in a period of rapid technological advancement. In order to promote and facilitate farmers' adoption of these technologies, the role of extension agents is essential. This study offers important insights into the variables influencing extension agents' decision-making processes regarding the use of digital technologies by utilizing the Theory of Planned Behaviour (TPB). The multifaceted nature of adoption behaviour is highlighted by the significant predictors of adoption behaviour including intention and perceived behavioural control and by extension attitudes and subjective norm on intention. Creating methods that effectively encourage the adoption of digital technologies in agricultural extension requires an understanding of the views and motivations of extension agents. A better understanding of elements including organizational support, perceived technology utility, and training needs can help extension agents increase their readiness to accept incorporating digital tools into their work.

This study highlights the necessity of customized interventions and capacity building programmes that support extension agents to successfully use digital technology. Agricultural extension programmes can increase their impact and hasten the adoption of creative solutions across varied farming communities by matching interventions with agents, beliefs, attitudes and contextual circumstances. In the end, stakeholders in agriculture especially the Ministry of Food and Agriculture can harness the transformative potential of digital technologies to drive agricultural development, improve food security, and promote sustainable livelihoods in rural communities by creating a supportive environment and provide extension agents with the necessary tools and resources. This study advances our knowledge of how agricultural extension agents adopt new technologies and emphasizes the value of enabling extension workers to act as change agents in the digital era.

ACKNOWLEDGEMENTS

The authors greatly appreciate the agricultural extension agents who contributed to the study by providing data for the analysis. We also thank the Directors of Agriculture of the various Departments who supported with the data collection. We wish to especially thank the data collection coordinators who oversaw the data collection.

INSTITUTIONAL REVIEW BOARD STATEMENT

This study was carried out based on the Declaration of Helsinki and approved by the Ethical Review Board of the University of Education, Winneba (reference code PVC/B.11/VOL.1/14 approved on March 13, 2023).

REFERENCES

Abdulai, A. R., Quarshie, P. T., Duncan, E., and Fraser, E. 2023. Is agricultural digitization a reality among smallholder farmers in Africa? Unpacking farmers' lived realities of engagement with digital tools and services in rural Northern Ghana. Agriculture & Food Security, 12(11): 1–14.

Ahsan, M. B., Leifeng, G., Azam, F. M. S., Xu, B., Rayhan, S. J., Kaium, A. and Wensheng, W. 2023. Barriers, challenges, and requirements for ICT usage among Sub-assistant agricultural officers in Bangladesh: Toward sustainability in agriculture. Sustainability (Switzerland), 15(782): 1–27.

Ajzen, I. 1991. The Theory of Planned Behavior. Organizational Behavior and Human Decision Processes, 50, 179–211.

Aliabadi, V., Gholamrezai, S. and Ataei, P. 2020. Rural people's intention to adopt sustainable water management by rainwater harvesting practices: application of TPB and HBM models. Water Supply, 20(5): 1847–1861.

Annor-Frempong, F. and Akaba, S. 2020. Socio-economic impact and acceptance study on drone-applied pesticides on maize in Ghana. Technical Report ISBN: 978-92-9081-673-7

Annor-Frempong, F., Kwarteng, J., Agunga, R. and Zinnah, M. M. 2006. Challenges and prospects of infusing Information Communication Technologies (ICTs) in extension for agricultural and rural development in Ghana. AIAEE 22nd Annual Conference Proceedings, 36–46.

Asante, I. K., Inkoom, E. W., Ocran, J. K., Kyeremateng, E., Sabari, G. and Odamtten, F. T. 2023. Intention of smallholder maize farmers to adopt integrated pest management practices for fall armyworm control in the Upper East region of Ghana. International Journal of Pest Management, 1–18.

Asante, I. K., Ocran, J. K., & Inkoom, E. W. (2023). Modeling pesticide use behavior among farmers in the Upper East Region of Ghana: An empirical application of the Theory of Planned Behavior. Environmental Protection Research, 3(1): 130–

149.

Atengdem, P. B., Fiafor, B., Tah, C. and Perkins, K. 2022. Agricultural e-extension services in Ghana: Strategy and plan (2022-2030). Farm Radio International. https://farmradio.org/publications/e-extension-services-in-ghana-strategy-and-plan/

Bagheri, A., Emami, N. and Damalas, C. A. 2021. Farmers' behavior towards safe pesticide handling: An analysis with the theory of planned behavior. Science of the Total Environment, 751(141709): 1–9.

Bagozzi, R. P., Yi, Y. and Phillips, L. W. 1991. Assessing construct validity in organizational research. Administrative Science Quarterly, 36(3): 421–458.

Baydur, H., Eser, E., Sen Gundogan, N. E., Ayhan, E., Eser, S., Dede, B., Hazneci, E., Öztekin, Y. B., Ekuklu, G., Cevizci, S. and Van den Broucke, S. 2023. Psychological determinants of Turkish farmers' health and safety behaviors: An application of the Extended Theory of Planned Behavior. Agriculture (Switzerland), 13(5).

Bishop, P. A. and Herron, R. L. 2019. Use and misuse of the Likert item responses and other ordinal measures. Journal of Chemical Information and Modeling, 53(9): 1689–1699.

Bosompem, M. 2021. Potential challenges to precision agriculture technologies development in Ghana: scientists' and cocoa extension agents' perspectives. Precision Agriculture, 22(5): 1578–1600

Carfora, V., Cavallo, C., Caso, D., Del Giudice, T., De Devitiis, B., Viscecchia, R., Nardone, G. and Cicia, G. 2019. Explaining consumer purchase behavior for organic milk: Including trust and green self-identity within the theory of planned behavior. Food Quality and Preference, 76: 1–9.

Chen, H., & Kuo, H. (2022). Green energy and water resource management: A case study of fishery and solar power symbiosis in Taiwan. Water, 14(1299), 1–15

Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Lawrence Erlbaum Associates, Publishers.

Damalas, C. A. 2021. Farmers' intention to reduce pesticide use: the role of perceived risk of loss in the model of the planned behavior theory. Environmental Science and Pollution Research, 28(26): 1–8.

Danso-Abbeam, G., Ehiakpor, D. S. and Aidoo, R. 2018. Agricultural extension and its effects on farm productivity and income: Insight from Northern Ghana. Agriculture and Food Security, 7(1): 1–10.

Davis, F. D. 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3): 319–339

Daxini, A., Ryan, M., O'Donoghue, C. and Barnes, A. P. 2019. Understanding farmers' intentions to follow a nutrient management plan using the theory of planned behaviour. Land Use Policy, 85: 428–437

Dibaba, B. and Biazin, H. 2022. Agricultural Extension Service in Ethiopia: The role of social system and farmers' - agricultural development agents relationship. American Journal of IT and Applied Sciences Research, 1(5): 1–15.

Dong, H., Wang, H., & Han, J. (2022). Understanding ecological agricultural technology adoption in China using an Integrated Technology Acceptance Model—Theory of Planned Behavior Model. Frontiers in Environmental Science, 10: 1–11.

El Bilali, H., & Allahyari, M. S. (2018). Transition towards sustainability in agriculture and food systems: Role of information and communication technologies. Information Processing in Agriculture, 5(4): 456–464

Fishbein, M. and Ajzen, I. 1975. Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research. Addison-Wesley. https://people.umass.edu/aizen/f&a1975.html

Fishbein, M. and Ajzen, I. 2010. Predicting and changing behavior: The reasoned action approach. Psychology Press under Taylor & Francis Group.

Gefen, D., Straub, D. and Boudreau, M.-C. 2000. Structural equation modeling and regression: Guidelines for research practice. Communications of the Association for Information Systems, 4(7): 1–78.

Geisser, S. (1974). A predictive approach to the random effect model. Biometrika, 61(1): 101–107.

Ghali-zinoubi, Z. 2022. Examining drivers of environmentally conscious consumer behavior: Theory of planned behavior extended with cultural factors. Sustainability, 14(8072): 1–17.

Gholamrezai, S., Aliabadi, V. and Ataei, P. 2021. Understanding the pro-environmental behavior among green poultry farmers: Application of behavioral theories. Environment, Development and Sustainability, 23: 16100–16118.

Govindharaj, G., Gowda, B., Sendhil, R., Adak, T., Raghu, S., Patil, N., Mahendiran, A., Chandra, P., Kumar, G. A. K. and Damalas, C. A. 2021. Determinants of rice farmers' intention to use pesticides in eastern India: Application of an extended version of the planned behavior theory. Sustainable Production and Consumption, 26: 814–823.

Hair, J. F., Hult, G. T. M., Ringle, C., Sarstedt, M., Danks, N., and Ray, S. 2021. Partial least squares structural equation modeling (PLS-SEM) using R: A workbook. Springer Nature Switzerland.

Hair, J. F., Ringle, C. M. and Sarstedt, M. 2011. PLS-SEM: Indeed a silver bullet. Journal of Marketing Theory and Practice, 19(2): 139–152.

Hair, J. F., Risher, J. J., Sarstedt, M. and Ringle, C. M. 2019. When to use and how to report the results of PLS-SEM. Psychometrika, 31(1): 2–24.

Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. Industrial Management and Data Systems, 117(3), 442–458.

Hair Jr, J., Hult, G. T., Ringle, C., & Sarstedt, M. (2017). A primer on partial least squares structural equation modeling (PLS-SEM) (2nd ed.). SAGE Publications Inc.

Hall, J. 2011. Cross-sectional survey design. In P. J. Lavrakas (Ed.), Encyclopedia of Survey Research Methods (pp. 173–178). Sage Publications, Inc.

Hayes, A. F. and Coutts, J. J. 2020. Use Omega rather than Cronbach's alpha for estimating reliability. But…. Communication Methods and Measures, 00:1–24.

Henseler, J., Ringle, C. M. and Sarstedt, M. 2015. A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1): 115–135.

Hulland, J. 1999. Use of partial least squares (PLS) in strategic management research: A review of four resent studies. Strategic Management Journal, 20(2): 195–204.

Hur, G., Barry, D. M., Alford, K., Jagger, C. B. and Roberts, T. G. 2024. Why pursue a career in teaching agriculture?: Application of Self-Determination Theory and the Theory of Planned Behavior. Journal of Agricultural Education, 65(2): 15–34.

Ibrahim, F. M., Osikabor, B., Olatunji, B. T. and Ogunwale, G. O. 2022. Understanding forest land conversion for agriculture in a developing country context : An application of the theory of planned behaviour among a cohort of Nigerian farmers. Folia Forestalia Polonica, Series A – Forestry, 64(3): 117–130

Jakku, E., Fielke, S., Fleming, A. and Stitzlein, C. 2022. Reflecting on opportunities and challenges regarding implementation of responsible digital agri-technology innovation. Sociologia Ruralis, 62(2): 363–388.

Karapandzin, J., Rodić, V. and Caracciolo, F. 2019. Factors affecting farmers' adoption of integrated pest management in Serbia: An application of the theory of planned behavior. Journal of Cleaner Production, 228: 1–27.

Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. Educational and Psychological Measurement, 30, 607–610.

Lai, P. (2017). The literature review of technology adoption models and theories for the novelty technology. Journal of Information Systems and Technology Management, 14(1): 21–38.

Lee, C. S., Chen, Y. C., Tsui, P. L. and Chiang, M. C. 2023. Using the Theory of Planned Behavior to examine the sustainable extension of rural food preparation techniques. Agriculture (Switzerland), 13(5). h

Loha, K. M., Klous, G., Lamoree, M. and Boer, J. De. 2022. Pesticide use and practice of local farmers in the Central Rift Valley (CRV) of Ethiopia: implications for the environment and health hazards. International Journal of Pest Management, 0(0), 1–14.

Markets and Markets. 2024. Digital agriculture market offering, technology (peripheral, core), operation (farming & feeding, monitoring &scouting, marketing & demand generation) type (hardware, software, services), region – Global forecast to 2028: Report Code AGI 8180. https://www.marketsandmarkets.com/Market-Reports/digital-agriculture-market-235909745.html

McEachan, R. R. C., Conner, M., Taylor, N. J. and Lawton, R. J. 2011. Prospective prediction of health-related behaviours with the theory of planned behaviour: A meta-analysis. Health Psychology Review, 5(2): 97–144.

Memon, M. A., Ramayah, T., Cheah, J.-H., Ting, H., Chuah,

F. and Cham, T.-H. 2023. Addressing common method bias, operationalization, sampling, and data collection issues in quantitative research: Review and recommendations. Journal of Applied Structural Equation Modeling, 7(2): i–xiv.

Ministry of Local Government and Rural Development. 2023. Background of regions in Ghana. Ghana Districts. http://www.ghanadistricts.com/

MoFA-DAES. 2021. Directorate of agricultural extension services 2021 report.

MoFA-Directorate of Agricultural Extension Services. 2003. Agricultural extension approaches being implemented in Ghana. mofa.gov.gh/site/wp-%0Acontent/uploads/2011/03/Extension-approaches-in-Ghana-.pdf

Moon, M. A., Mohel, S. H. and Farooq, A. 2019. I green, you green, we all green: Testing the extended environmental theory of planned behavior among the university students of Pakistan. Social Science Journal, 58(3): 1–12.

Nunnally, J. C. 1978. Psychometric theory. McGraw-Hill.

Nyarko, D. A. and Kozári, J. 2021. Information and communication technologies (ICTs) usage among agricultural extension officers and its impact on extension delivery in Ghana. Journal of the Saudi Society of Agricultural Sciences, 20(3): 164–172.

Ocran, J. K., Asante, I. K. and Ametepey, K. T. E. 2024. Benefits, barriers, challenges and requirements for the application of digital technologies in agricultural extension in selected regions in Ghana: Perspectives from extension agents. Journal of Agricultural Extension and Rural Development, 16(2): 88–105.

Omega, S., Annor-Frempong, F., Akaba, S., Ghartey, W., Ocran, J. K. and Asante, I. K. 2020. Willingness to pay for drone technology in the application of pesticides for control of FallArmy Worm. Paper Presented at the 1st African Conference on Precision Agriculture, 353–356.

Ortiz-Crespo, B., Steinke, J., Quirós, C. F., van de Gevel, J., Daudi, H., Gaspar Mgimiloko, M. and van Etten, J. 2021. User-centred design of a digital advisory service: enhancing public agricultural extension for sustainable intensification in Tanzania. International Journal of Agricultural Sustainability, 19(5–6): 566–582.

Prince, M. and Das-Munshi, J. 2020. Cross-sectional surveys. In J. Das-Munshi, T. Ford, M. Hotopf, M. Prince, & R. Stewart (Eds.), Practical Psychiatric Epidemiology (Online, pp. 127–144). Oxford University Press.

Quintal, V. A., Lee, J. A. and Soutar, G. N. 2010. Risk, uncertainty and the theory of planned behavior: A tourism example. Tourism Management, 31(6): 797–805.

Rajeh, M. T. 2022. Modeling the theory of planned behavior to predict adults' intentions to improve oral health behaviors. BMC Public Health, 22(1391), 1–9.

Rezaei, R., Seidi, M. and Karbasioun, M. 2019. Pesticide exposure reduction: Extending the theory of planned behavior to understand Iranian farmers' intention to apply personal protective equipment. Safety Science, 120: 527–537.

Ringle, C. M., Wende, S. and Becker, J. M. 2022. SmartPLS 4 (4.0; pp. 1–225). SmartPLS GmbH. www.smartpls.com

Rogers, E. M. 2003. Diffusion of innovations (5th ed.). Free Press. https://www.worldcat.org/title/diffusion-of-innovations/oclc/52030797

Sarstedt, M., Hair, J. F., Nitzl, C., Ringle, C. M., & Howard, M. C. (2020). Beyond a tandem analysis of SEM and PROCESS: Use of PLS-SEM for mediation analyses! International Journal of Market Research, 62(3): 288–299.

Sarstedt, M., Ringle, C. M. and Hair, J. F. 2021. Handbook of market research. In C. Homburg, M. Klarmann, & A. E. Vomberg (Eds.), Handbook of Market Research (pp. 1–47). Springer, Cham.

Shiau, W. L., Sarstedt, M. and Hair, J. F. 2019. Internet research using partial least squares structural equation modeling (PLS-SEM). Internet Research, 29(3): 398–406.

Shirahada, K. and Zhang, Y. 2022. Counterproductive knowledge behavior in volunteer work: perspectives from the theory of planned behavior and well-being theory. Journal of Knowledge Management, 26(11): 22–41.

Shmueli, G. and Koppius, O. R. 2011. Predictive analytics in information systems research. MIS Quarterly: Management Information Systems, 35(3): 553–572.

Shmueli, G., Ray, S., Velasquez Estrada, J. M. and Chatla, S. B. 2016. The elephant in the room: Predictive performance of PLS models. Journal of Business

Research, 69(10): 4552–4564.

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., Vaithilingam, S. and Ringle, C. M. 2019. Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. European Journal of Marketing, 53(11): 2322–2347

Şimşek, G. G. and Noyan, F. 2013. McDonald's ω t , Cronbach's α, and Generalized θ for Composite Reliability of Common Factors Structures . Communications in Statistics - Simulation and Computation, 42(9): 2008–2025.

Sniehotta, F. F., Presseau, J. and Araújo-Soares, V. 2014. Time to retire the theory of planned behaviour. Health Psychology Review, 8(1): 1–7.

Stone, M. 1974. Cross - validatory choice and assessment of statistical predictions. Journal of the Royal Statistical Society: Series B (Methodological), 36(2): 111–133

Tian, X., Xu, P., Liu, X. and Xu, X. 2023. The impact of digital information treatment on the evaluation of service performance of agricultural extension agents. Information Development, 0: 1–16.

Tsan, M., Totapally, S., Hailu, M. and Addom, B. K. 2019. The digitalisation of African Agriculture Report (2018-2019) (J. Lichtenstein, M. Schnapf, & B. Beks (eds.); 1st ed.). The Technical Centre for Agricultural and Rural Cooperation (CTA). https://cgspace.cgiar.org/bitstream/handle/10568/101498/CTA-Digitalisation-report.pdf

Uzun, V., Shagaida, N. and Lerman, Z. 2019. Russian agriculture: Growth and institutional challenges. Land Use Policy, 83: 475–487.

VanderStoep, S. W. and Johnston, D. D. 2009. Research Methods for everyday life: Blending Qualitative and Quantitative Approaches (1st ed.). Jossey-Bass of John Wiley & Sons, Inc. www.josseybass.com

Venkatesh, V. and Bala, H. 2008. Technology acceptance model 3 and a research agenda on interventions. Decision Sciences, 39(2): 273–315.

Venkatesh, V. and Davis, F. D. 2000. Theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. Management Science, 46(2): 186–204.

Vonglao, P. 2017. Application of fuzzy logic to improve the Likert scale to measure latent variables. Kasetsart Journal of Social Sciences, 38(3): 337–344.

Wastutiningsih, S. P. and Aulia, D. 2023. Influence sustainable consumption campaigns on intention to perform food waste reduction behavior of young consumers in Yogyakarta. In book: Proceedings of the International Conference On Multidisciplinary Studies (ICOMSI 2022) (pp.335-343)

Xu, Y., Lyu, J., Xue, Y. and Liu, H. 2022. Intentions of farmers to renew productive agricultural service contracts using the Theory of Planned Behavior: An empirical study in Northeastern China. Agriculture (Switzerland), 12(9).

Yuriev, A., Dahmen, M., Paillé, P., Boiral, O. and Guillaumie, L. 2020. Resources, conservation & recycling pro-environmental behaviors through the lens of the theory of planned behavior: A scoping review. Resources, Conservation & Recycling, 155(104660): 1–12.

Zaremohzzabieh, Z., Krauss, S. E., D'Silva, J. L., Tiraieyari, N., Ismail, I. A. and Dahalan, D. 2022. Towards agriculture as career: predicting students' participation in the agricultural sector using an extended model of the theory of planned behavior. Journal of Agricultural Education and Extension, 28(1): 67–92.