

## RESEARCH ARTICLE

# Adoption of climate-smart agricultural practices by smallholder farmers in rural Ghana: An application of the theory of planned behavior

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## Abstract

Climate-Smart Agricultural (CSA) practices are crucial in managing climatic shocks faced by smallholder farmers in sub-Saharan Africa. However, evidence on the socio-psychological drivers of farmers' adoption of CSA practices remains limited. This study employed the Theory of Planned Behavior framework to analyze smallholder farmers' intention and adoption behavior toward CSA practices in rural Ghana. The study sampled 350 smallholder farmers from the Upper East and North-East Regions of Ghana and employed the Structural Equation Model to understand smallholder farmers' intention and adoption behavior toward CSA practices. Results showed that farmers' attitudes (notably their beneficial evaluation of CSA practices) had a significant impact (0.25) on their intention to adopt CSA practices. Social pressure exerted on farmers to use CSA practices (Subjective norm) also had a significant impact (0.52) on farmers' adoption behavior. Perceived behavior control which measures the controllability and use of CSA practices also had a significant impact on both the intention (0.43) and adoption behavior (0.20) of smallholder farmers. Findings highlight the role socio-psychological factors play in explaining the adoption of CSA practices in rural Ghana. We recommend the need to create awareness of CSA practices by sharing relevant information more widely on CSA practices through community leaders, chief farmers, assembly members, and clan heads in order to exert influence on farmer's adoption of CSA practices.

## 1. Introduction

Increased rainfall variability and drought associated with climate change poses the greatest challenge to the food systems and sustainable agricultural development of sub-Saharan Africa (SSA) [1, 2] and to the region's food and nutrition security [3]. SSA is regarded as the most

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vulnerable region to the negative impacts of climate change, because of structural and institutional weakness, high poverty levels and the low adoption of modern techniques that limits farmers' capacity to adapt [4–6].

Agriculture in Ghana, like most SSA countries is largely rainfall-dependent and employs about 75% of the rural population [7], but extreme weather events arising from climate change pose a serious threat to the agricultural sector and agri-based livelihoods. Projections from climate models point to a worsening situation in Ghana. For example [8], reported that the annual mean temperature is projected to increase by 2.0°C and 3.9°C while rainfall is also projected to decrease by 10.9% and 18.6% by the years 2050 and 2080, respectively. Historical data indicate a worrying trend of shifting climatic conditions that encompass erratic and declining rainfall patterns and a warming trend across all the agro-ecological zones of Ghana [9]. These climatic changes are estimated to reduce cassava and rice yields by 13.5% and 8% by the year 2050 [10]. As such, crop yields will continue to decline unless farmers adopt and utilize Climate-Smart Agricultural (CSA) practices [11].

Climate-Smart Agriculture aims to achieve three pillars: (1) sustainably increase agricultural productivity and incomes; (2) enhance farmers' adaptive capacity and build resilience; and (3) reduce the emission of greenhouse gases (GHGs) [12, 13]. It has become imperative for farmers in developing countries to adopt and use CSA practices since they include numerous inexpensive farm-based sustainable agricultural land management techniques such as water management, zero/minimum tillage, residue management, and agroforestry among others. Additionally, CSA practices mostly include traditional practices and indigenous knowledge that are widely known to, and used by, farmers in addressing climatic risks [3, 14].

Ghana, like many SSA countries, has sought to promote CSA through its sustainable agricultural development policy [15]. A National Climate-Smart Agriculture and Food Security Action Plan was developed with the aim of facilitating and operationalizing the National Climate Change Policy for effective incorporation of climate change into food and agriculture sector development policies and programs [16]. The action plan sought to provide a multi-sectoral institutional mechanism for climate-smart agriculture [16]. Over the years, numerous efforts have been made by the Government of Ghana and international organizations to promote the adoption of CSA practices to help mitigate the impact of climate change [17, 18]. Despite these efforts CSA adoption remains low among smallholder farmers in many parts of Ghana [19]. However, the few farmers that have adopted practices attest to their effectiveness in increasing farm productivity and incomes, enhancing food security, and conserving the natural resources in Ghana [20–22].

Several studies have examined the determinants of the adoption and impact of CSA practices in SSA countries [23–25] and in Ghana specifically [20, 22, 26]. The determinants identified by these studies were mostly socio-demographic factors. Other determinants identified were access to extension services, awareness of climate change/variability, agricultural insurance, membership of farmer-based organization, and location of the farmer. Some adoption-related studies identified economic incentives as the major determining factor of the adoption of climate smart agricultural practices [27, 28]. However, the factors affecting adoption of agricultural practices goes beyond just socio-demographic factors and economic incentives and are largely influenced by individual and intrinsic motivations [29, 30] and other perceptions which can best be explained by psychological theories [31, 32]. As yet, there is a dearth of empirical studies on the influence of individual and intrinsic motivation on the adoption of CSA practices in SSA and Ghana in particular. This study addresses this gap by using the Theory of Planned Behavior developed by [33] to examine the behavioral intention and actual adoption behavior of smallholder farmers toward CSA practices in Ghana. The Theory of Planned Behavior was chosen for this work because it provides socio-psychological basis for

understanding human behavior [34, 35] in diverse fields to encourage behavior change [36]. The main aim of the study was to identify the socio-psychological factors that influence farmers' behavioral intention and actual behavior towards the adoption of CSA practices in rural Ghana using the Theory of Planned Behavior. The specific objectives of this study were to:

1. Determine which psychological factors exert greater influence on farmers' behavioral intention and behavior towards the adoption of CSA practices in rural Ghana.
2. Examine whether farmers' behavioral intention towards CSA practices translate into actual adoption behavior of CSA practices in rural Ghana.

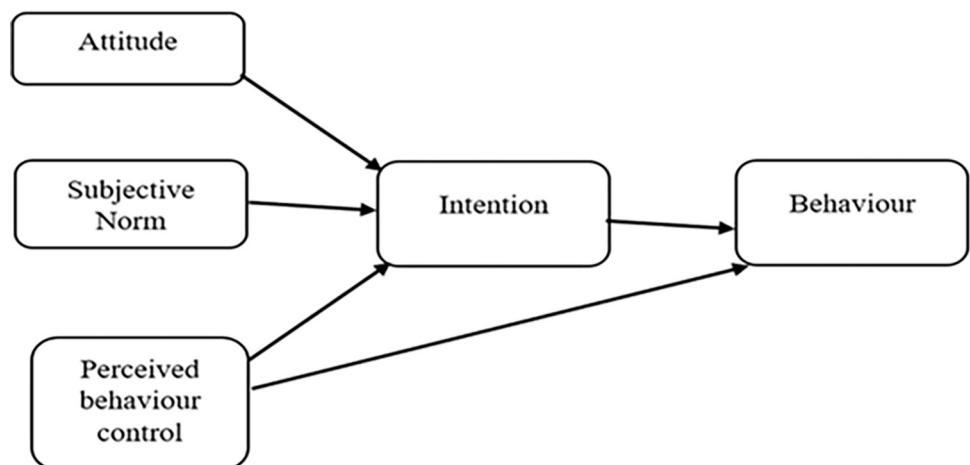
We contribute to the literature on the adoption of CSA practices by identifying the relative significance of the Theory of Planned Behavior constructs on farmers' behavioral intention and adoption behavior towards CSA practices in dryland farming systems. Insights can inform policymakers the areas of possible interventions that can be impactful at the household level to positively alter farmers' behavior and enhance their adoption of CSA practices.

## 2. Theoretical framework and hypotheses development

### 2.1. The theory of planned behavior

This study aimed to explain the adoption of CSA practices using the Theory of Planned Behavior (TPB) as developed by [33] (Fig 1). Although a plethora of studies indicate the importance of economic incentives in driving the adoption behavior of farmers [31, 37–39], the TPB has proven valuable in explaining the decision-making process of farmers [40, 41]. This is because farmers are not only profit-maximizing entities [42], but can be influenced by other individual and intrinsic motivations especially when the decision may have both social and environmental consequences [29, 30]. The TPB predicts people's intention to follow a particular behavior based on the assumption that human behavior is regulated by behavioral intentions which are determined by the attitude, subjective norm, and perceived behavior control of individuals [33, 43; Fig 1].

The behavior intention of a farmer can be defined as that farmer's motivation regarding their plan or conscious decision to apply effort to carry out a particular behavior [44, 45]. Behavior intention represents the immediate antecedent and best predictor of performing an actual behavior [33]. By implication, stronger behavior intention towards a behavior indicates



**Fig 1. Theory of planned behavior.** Source: [33].

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a stronger likelihood of performance of that behavior [46]. Such behavioral intention can accurately be estimated from the farmer's attitude towards that particular behavior, subjective norm, and perceived behavior control [33, 43]. However, limited studies [47, 48] have examined the relationship between behavior intention and actual behavior due to the difficulty in measuring actual behavior. In addressing this, our study used past adoption behavior as a proxy for future adoption behavior particularly because farmers' adoption of CSA practices shows a high degree of temporal stability [47, 49].

Attitude refers to the favorable or unfavorable assessment of behavior. The overall assessment of behavior and belief in its desired results determine the attitude towards a behavior [50]. By implication, a more positive attitude towards a behavior leads to a better intention of carrying out that behavior [51]. Several studies [47, 52, 53] have indicated the role of attitude in predicting farmers' intention to adopt farm practices. Attitude can be regarded as a significant determinant of an individual's intention and behavior [54, 55].

Subjective norm includes perceived social influence from internal and/or external sources to carry out or not to carry out a particular behavior. Such pressure may arise from internal sources such as family members and relatives or external sources such as friends and personnel from a government agency or an NGO [56]. The perceived approval of behavior by important people within a community also serves as a source of pressure that induces individuals' intention of performing that particular behavior [57]. Subjective norm, therefore, measures the influence of the society on the decision-making process of a farmer [58]. Subjective norm has been estimated to be the most important determining factor of farmers' intention to adopt new practices [59–61].

Perceived behavior control relates to the perceived ease or difficulty in performing a particular behavior. Perceived behavior control concerns itself with the existence of control factors that may hamper or enable the performance of a particular behavior [43]. These control factors may be in the form of money, skills, time as well as cooperation with others [62] and these may determine the farmers' ability to carry out a particular behavior. A farmer's engagement in a given behavior is subject to the farmer's belief in the likelihood of having access to the required resources and opportunities [44]. Perceived behavior control is an essential predictor of farmers' intention to adopt farm practices [60, 63, 64]. By extension, Perceived Behavior Control has a direct influence on intention and behavior [54, 65].

**Hypotheses.** Based on the TPB model, seven hypotheses were developed for the study as follows:

- H<sub>1</sub>: Attitude has a positive influence on farmers' intention to adopt CSA practices.
- H<sub>2</sub>: Subjective norm has a positive influence on farmers' intention to adopt CSA practices.
- H<sub>3</sub>: Perceived behavior control has a positive influence on farmers' intention to adopt CSA practices.
- H<sub>4</sub>: Behavioral intention mediates the positive effects of attitude, subjective norm, and perceived behavior control on farmers' adoption of CSA practices.
- H<sub>5</sub>: Attitude has a positive influence on farmers' adoption of CSA practices.
- H<sub>6</sub>: Subjective norm has a positive influence on farmers' adoption of CSA practices.
- H<sub>7</sub>: Perceived behavior control has a positive influence on farmers' adoption of CSA practices.

The TPB was extended with additional two hypotheses (H<sub>5</sub> and H<sub>6</sub>) which showed a direct relationship between attitude and behavior, and subjective norm and behavior. Sapp et al. [66] argue that, behavior intentions may be ill-informed at certain times leading to inconsistency between intention and actual behavior. It is therefore critical to examine the attitude–behavior and subjective norm–behavior relation to provide a better understanding of their impact on actual behavior because such relation has been largely ignored in the literature. Studies such as

[67, 68] have asserted that psychological factors such as attitudes and subjective norms are not always mediated by intention but can have a direct influence on actual behavior.

### 3. Methodology

#### 3.1. Study area

The study was carried out in the West Mamprusi Municipality in the North East Region, and the Bongo District and Bolgatanga Municipality in the Upper East Region of Ghana (Fig 2). These districts lie within the Sudan savannah agro-ecological zone and have a single rainfall pattern that lasts from May/June to September/October.

The West Mamprusi Municipality lies between longitudes 0°35' W and 1°45' W and latitudes 9°55' N and 10°35' N. The municipality has a total population of 175,755, comprising 85,712 males and 90,043 females [69]. West Mamprusi municipality is rural with agriculture being the mainstay of the local economy [70]. The main agricultural activities in the municipality include the rearing of livestock and the production of maize, millet, sorghum, and groundnuts.

The Bongo District is located between longitudes 0°W and 1°30'W and latitudes 10°30'N and 11°N. The Bongo district has a total population of 120,254, comprising 56,920 males and 63,334 females [69]. Subsistence agriculture involving the production of sorghum, millet, rice, groundnuts, and maize is the main economic activity in the district [71].

The Bolgatanga Municipality is located between longitudes 0°30'W and 1°00'W and latitudes 10°30'N and 10°50'N. The Bolgatanga Municipality has a total population of 139,864, comprising 66,607 males and 73,257 females. Despite being a relatively urbanized municipality, livestock farming and crop production continue to be the main economic activity employing over 60% of the labor force within the municipality [72].

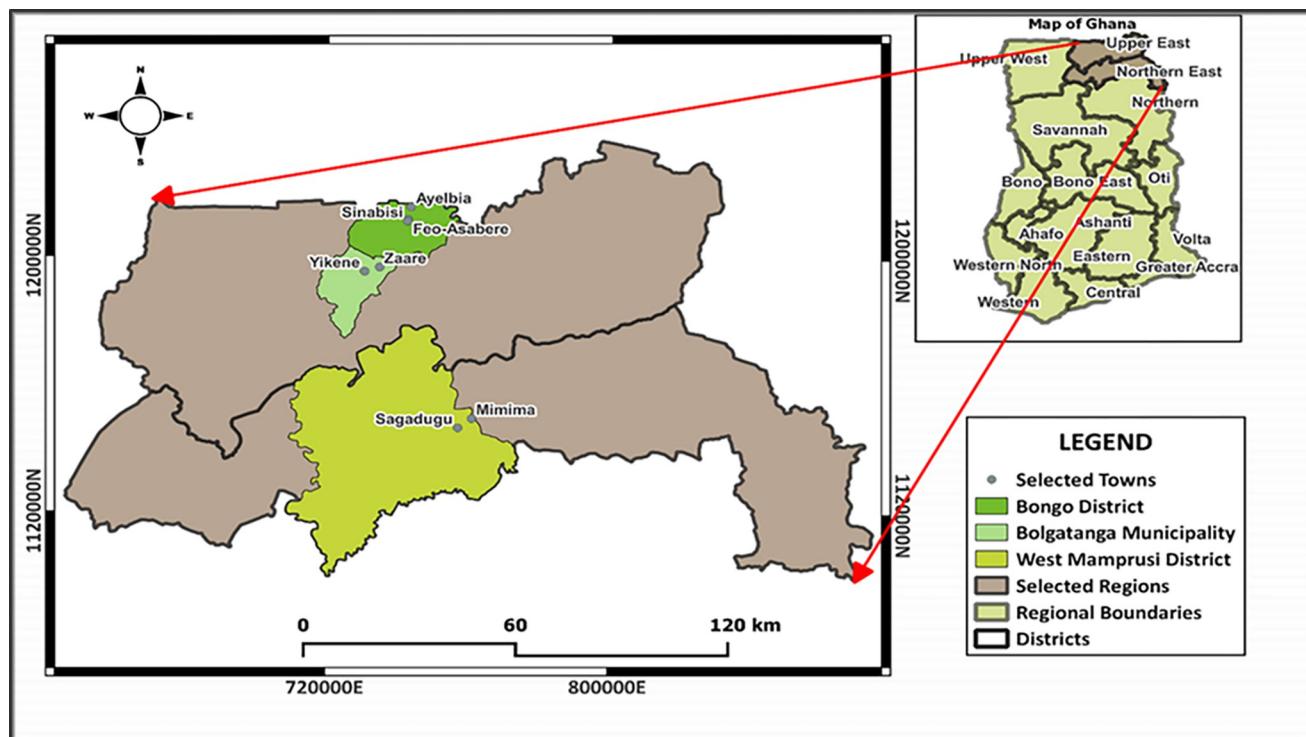


Fig 2. Map showing study communities.

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These districts were selected because they are among the most vulnerable to drought in Ghana and the majority of the populace are dependent on rain-fed agriculture for their livelihood [73, 74]. Consequently, several projects and interventions such as the knowledge systems and advisory services supporting CSA aimed at enhancing farmers' adoption of CSA practices have been instituted in these areas.

### 3.2. Sampling procedure

Three districts, namely West Mamprusi Municipality in the North East Region and Bongo District and Bolgatanga Municipality in the Upper East Region of Ghana, which have significant rural populations with agriculture as the main source of livelihoods were purposively selected. These districts were selected because they host several CSA demonstration fields of the Ghana Agricultural Sector Investment Program (GASIP). Subsequently, with the assistance of district agricultural officers, Sagadugu and Mimima in the West Mamprusi Municipality, Yikene and Zaare in the Bolgatanga Municipality, and Ayelbia, Sinabisi, and Feo-Asabere in the Bongo District were selected.

Three hundred and fifty (350) household surveys were conducted in the seven study communities. A total of 87 households (38 in Sagadugu and 49 in Mimima) were interviewed in the West Mamprusi Municipality. Eighty-eight (88) households (46 in Ayelbia, 20 in Sinabisi and 22 in Feo-Asabere) were interviewed in the Bongo District while 175 households (87 in Yikene and 88 in Zaare) were interviewed in the Bolgatanga Municipality.

### 3.3. Ethics statement

Ethical approval for this study was provided by the Humanities and Social Sciences Research Committee (HuSSRECC) of the Kwame Nkrumah University of Science and Technology, Ghana. HuSSRECC subjected the protocol to a thorough review and, among other things, observed that the necessary precautions have been taken to ensure that the participants in study will be well protected from risks and other distasteful occurrences they may face in the administration of questionnaire in particular. Formal consent for participation was obtained verbally from each study participant after the study objectives have been interpreted to them in their local dialect. Study participants were assured of anonymity and confidentiality.

### 3.4. Questionnaire design and measurement scale

Smallholder farmers were randomly selected using the Census and Survey Processing System (CSPro) software in the seven farming communities. The survey was conducted between August 2021 and September 2021 using locally trained enumerators. Interviews were conducted at the convenience of the farmers at their homes and lasted between 45 to 60 minutes. The survey instrument consisted of a questionnaire that solicited information on the socio-demographic characteristics of the respondents, and questions framed base on the theory of planned behavior about CSA practices (S1 File). Four of the latent constructs (i.e. behavioral intention, attitude, subjective norm, and perceived behavioral control) were measured using twenty-two items adopted and modified from [75, 76]. A five-point Likert scale was used for all the items (Part 1 in S1 File).

Following the TPB guidelines, constructs for behavioral intention, attitude, subjective norm, and perceived behavioral control followed the principle of compatibility to avoid the occurrence of weaker and less-robust correlations among the constructs [77]. These constructs were defined in terms of the same element (i.e., CSA practices) to ensure construct compatibility and we also ensured that measurement scales were compatible across study sites to achieve scale compatibility [34, 43]. Behavioral intention to adopt CSA practices was measured by four

items, which enquired about farmers' willingness to utilize CSA practices (with or without support) and their willingness to overcome barriers in terms of finance and information. Attitude towards CSA was measured using six items, three of which were concerned with the importance, convenience, and practicability of CSA practices. The other three considered the possible contributions of CSA practices in terms of increases in yield, on-farm income, and reputation. Subjective norm toward CSA was measured using six items, three of these items were about the motivation to use CSA practices while the other three covered the perception of others concerning adopting CSA practices.

Perceived behavior control was measured with six items. These items covered the control a farmer had over actions needed to adopt CSA practices. The fifth latent construct (CSA adoption) consisted of eight items covering CSA practices such as; the use of drought-tolerant varieties, cover cropping, zero tillage, no burning of crop residues, mixed cropping, planting early maturing varieties, water management/irrigation, and intercropping with legumes. A four-point Likert scale was used for these items.

### 3.5. Data analysis

The study used Structural Equation Modeling (SEM) with latent constructs to analyze the collected data following [59, 78, 79]. The first step involved Confirmatory Factor Analysis (CFA) to acquire a suitable measurement model. Step two covered the development and testing of the structural model. CFA was carried out to assess the validity of constructs as well as to evaluate the fitness of the model. [80, 81] indicate the need for conducting CFA because construct validity reveals the extent to which the measured items reflect the hypothetical construct they are intended to measure. The validity of the measurement model was assessed using the overall goodness-of-fit statistics. Overall goodness-of-fit was assessed by checking the chi-squared value, the root mean square error of approximation (RMSEA), the comparative fit index (CFI), and the standardized root mean square residual (SRMR) [59, 78]. Cronbach alpha and factor loadings were used to establish the reliability of the constructs and various items.

The structural modeling involved the estimation of a set of multiple regressions with particular emphasis on the nature and magnitude of the relation between the latent constructs [78, 81] in this case attitude (ATT), subjective norms (SN), perceived behavior control (PBC), behavioral intention (BI) and actual behavior (CSA adoption). The predictive power and the ability of the SEM to estimate multiple regressions simultaneously made it the appropriate tool to examine the causal relations that exist among the TPB constructs and to test the underlying hypotheses. The SEM was estimated using the maximum likelihood procedure because maximum likelihood estimation procedure has proven to produce reliable and robust results under different circumstances compared to other estimation procedures [82].

### 3.6. Limitations of the study methods

Disagreement from respondents on what constituted climate smart practices is a limitation of the current study. The researchers resolved this limitation by providing further explanations as to what CSA practices were and the goals they seek to achieve. Another limitation of the study was focusing solely on the original factors of the Theory of Planned Behavior in explaining adoption of CSA practices. However, the authors saw this as necessary due to the extensive literature available on other factors affecting adoption decision of farmers. In spite of the limitations, the current study has strengths in terms of measuring CSA practices by not limiting it to a simple yes/no response but by measuring the frequency of use of these practices. The use of a Likert scale in measuring the adoption helps to ensure that a farmer who uses any CSA practice on yearly basis has a greater adoption score than a farmer who rarely uses or had used the

given practice only once. Future study can build on this study by recategorizing the CSA practices under similar themes so as to measure the impact of the psychological factors on these sub-themes.

## 4. Results

### 4.1. Descriptive statistics

The demographic and socioeconomic information of farmers are presented in [Table 1](#). The majority of respondents are smallholder farmers with 68.9% estimated farm sizes to be 2 hectares or below.

### 4.2. Item measurement in the TPB model

[Table 2](#) presents descriptive statistics, factor loadings, and Cronbach alpha for the various constructs of the TPB framework. All the 350 respondents reported that they used at least one of the eight CSA practices most prevalent in their localities. A comparison of the eight items that make up the CSA adoption construct shows that mixed cropping (94.9%) was the most used practice followed by intercropping with legumes (82.9%), planting early maturing varieties (73.1%), no burning of crop residues (67.4%), cover cropping (62.6%), use of drought-tolerant varieties (60.9%), zero tillage (57.4%) and water management/irrigation (17.7%).

In terms of behavioral intention to adopt CSA practices, a cumulative 5% of the sample expressed disagreeable intention to adopt CSA practices while 3% showed neither agreeable nor disagreeable intention to adopt CSA practices. Item b1n6 (“I am willing to learn about CSA practices”) shows the highest mean score while item b1n1 (“I am willing to adopt CSA practices by myself; with or without financial support”) shows the least mean score.

**Table 1. Socioeconomic characteristics of study respondents.**

Variable	Description	Frequency	Percentage	Mean	Std deviation
Gender (0 = female; 1 = male)	Male	152	43.4	1.9	1.2
	Female	198	56.6		
Education	No formal education	174	49.7	1.9	1.2
	Basic education	128	36.6		
	Secondary education	37	10.6		
	Tertiary education	11	3.1		
Source of income	On-farm	286	81.7	1.2	0.4
	Off-farm	64	18.3		
Household size	≤ 5	82	23.4	8.9	5.0
	6–12	210	60		
	≥ 13	58	16.6		
Farm size (in hectares)	≤ 2	241	68.9	2.3	2.5
	3–10	104	29.7		
	≥ 11	5	1.4		
Age	≤ 30	95	27.1	39.5	12.1
	31–50	198	56.7		
	51–70	52	14.9		
	≥ 71	5	1.4		
Years of farming	≤ 5	80	22.9	16.1	12.0
	6–15	121	34.6		
	16–30	117	33.4		
	≥ 31	32	9.1		

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**Table 2. Descriptive statistics for CSA practices, behavioral intention, attitude, subjective norm and perceived behavior control of respondents towards the adoption of CSA practices.**

Construct/Items	Mean	SD	Factor loadings	Cronbach alpha
<i>CSA-adoption (average of CSA below)</i>	2.87	1.02		0.66
csa1: uses drought-tolerant crop varieties	2.67	1.13	0.75***	
csa2: cover cropping	2.81	1.22	0.77***	
csa3: intercropping with legumes	3.23	0.84	0.24***	
csa4: zero tillage	2.86	1.18	0.38***	
csa5: mixed cropping	3.67	0.64	0.26***	
csa6: planting early maturing varieties	3.04	1.14	0.18***	
csa7: water management/irrigation	1.62	0.96	0.25***	
csa8: no burning of crop residues	3.05	1.06	0.69***	
<i>Behavioral intention (average of BN below)</i>	4.38	0.84		0.64
b1n1: I am willing to adopt CSA practices by myself with or without financial support	4.08	1.04	0.46***	
b1n3: I am willing to access credit facilities to overcome financial barriers to CSA practices' adoption	4.34	1.08	0.52***	
b1n5: I am willing to receive information about CSA practices	4.52	0.66	0.76***	
b1n6: I am willing to learn about CSA practices	4.59	0.56	0.65***	
<i>Attitude (average of ATT below)</i>	4.44	0.72		0.78
att1: For me, CSA practices are important	4.57	0.60	0.63***	
att2: For me, CSA practices are convenient	4.29	0.93	0.34***	
att3: Implementing CSA practices on my farm is practicable	4.41	0.69	0.69***	
att4: I think CSA practices will increase crop yields on my farm	4.53	0.62	0.89***	
att5: I think CSA practices will increase my on-farm income	4.50	0.64	0.78***	
att6: I think adopting CSA practices will improve my reputation in the community	4.33	0.81	0.50***	
<i>Subjective norm (average of SN below)</i>	3.49	1.15		0.69
sn1: it is expected of me to integrate CSA practices in my farming since others are doing it	3.71	1.27	0.72***	
sn2: the opinion of important referents about CSA practices is important to me	3.88	1.05	0.88***	
sn4: I want to be like other farmers in my community when it comes to choosing CSA practices	4.05	0.87	0.66***	
sn6: CSA practices are something I speak about with important referents	4.10	0.93	0.52***	
sn8: I feel under pressure from extension agents to integrate CSA practices in my farming	2.58	1.41	0.19***	
sn9: people whom I respect will disapprove if I do not integrate CSA practices in my farming	2.61	1.34	0.19***	
<i>Perceived behavior control (average of PBC below)</i>	3.66	1.02		0.81
pbcl: if I wanted to, it is easy to integrate CSA practices in my farming	3.98	0.96	0.40***	
pbcl: I would be able to practice at least one of the CSA practices	3.35	0.70	0.56***	
pbcl: I have the resources to implement the CSA practices	3.22	1.40	0.72***	
pbcl: I can easily command to use CSA practices on my farm	3.93	0.98	0.80***	
pbcl: I can use CSA practices on my farm whenever I want	4.02	0.86	0.83***	
pbcl: I have all the information I need to adopt CSA practices on my farm	3.51	1.24	0.67***	

Note

\*\*\*, \*\*, and \* indicate statistical significance at 1%, 5% and 10%, respectively

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Farmers expressed a positive attitude (mean of 4.44) towards the adoption of CSA practices. The majority of farmers interviewed expressed an agreeable attitude towards the adoption of CSA practices. About 2% of the sample expressed a disagreeable attitude towards the adoption of CSA practices, while 6% seem indifferent about the adoption of CSA practices.

About 25% of the sample expressed disagreeable subjective norms towards the adoption of CSA practices while about 10% of the sample expressed neither disagreeableness nor agreeableness towards the adoption of CSA practices. Sn6 ("CSA practices are something I speak about with important referents") showed the highest mean score compared to sn8 ("I feel

**Table 3. Goodness-of-fit indices for (n > 250 and observed variables  $\geq 30$ ).**

Criteria	Norm	Observed value
$\chi^2 / df$	Significant p-values expected	Chi2 (395) = 1236.95, p > chi2 = 0.0000
CFI	> 0.92	0.925
RMSEA	< 0.07	0.069
SRMR	$\leq 0.08$	0.080

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under pressure from extension agents to integrate CSA practices in my farming”) which received the lowest mean score. In terms of perceived behavioral control, 15% of the sample indicated disagreeableness while about 9% indicated that they were neither agreed nor disagreed with the items under this construct. Pbc4 (“I have the resources to implement the CSA practices”) showed the least mean score while pbc5 (“I can easily command to use CSA practices on my farm”) showed the highest mean score.

Factor loadings from the confirmatory factor analysis (Table 2) show that the observed variables were significant at the  $p < 0.01$  level and can be considered adequate, ranging from 0.18 to 0.89. Although, six items recorded factor loadings less than 0.30 as recommended for a sample size of at least 350 [82], they were maintained because they were greater than 0.10 and proved to establish a simple structure [42, 82] and suggested at least good contributions of these items to their respective constructs [83]. The factor loadings (Table 2) indicate that all the five latent variables satisfied the convergent validity test. The Cronbach alpha which was used to test for the reliability of the constructs indicated that all five constructs—attitude, subjective norm, perceived behavior control, behavioral intention and CSA adoption—recorded Cronbach alpha of above 0.60, implying that measurement scales for all the variables were internally consistent and reliable [82, 84].

### 4.3. Goodness-of-fit statistics

Based on the “cut-off” points developed by [82] and presented in Table 3, we chose four measures namely: chi-squared/degrees-of-freedom ( $\chi^2 / df$ ), comparative fit index (CFI), root mean square error of approximation (RMSEA), and standardized root mean squared residual (SRMR) to determine the overall model fit. Although a significant  $\chi^2$  indicates an unfit model, this was expected due to the large sample size and a high number of observed variables hence the  $\chi^2$  is not sufficient to measure the overall fit of the model [82, 85, 86]. The CFI which is less sensitive to model complexity shows that the model is fit given the “cut off” point of 0.92 for large sample sizes [82]. The observed value for RMSEA which attempts to rectify the tendency of using  $\chi^2$  to reject models with large sample sizes [82, 87] indicates a good fit given an observed value of 0.069. The observed value of 0.08 for SRMR suggests no problem with the model fit indicating that the estimated model is significant and inferences made can be reliable [82, 88].

### 4.4. Hypotheses testing

Table 4 shows that the attitude, subjective norm, and perceived behavior control of smallholder farmers jointly explained 25% of the variations in farmers’ intention to adopt CSA

**Table 4. R-Squared for the equations.**

Endogenous variable	R <sup>2</sup>
BI	25%
CSA-use	30%

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Table 5. Summary of hypotheses test results based on the TPB.

Path (hypothesis)	Path coefficient	Std error	z-value	p-value	Evidence
ATT → BI (H <sub>1</sub> )	0.25***	0.09	3.49	0.000	Supported
SN → BI (H <sub>2</sub> )	0.02	0.03	0.30	0.765	Unsupported
PBC → BI (H <sub>3</sub> )	0.43***	0.13	3.97	0.000	Supported
BI → CSA-adoption (H <sub>4</sub> )	-0.07	0.14	-0.93	0.354	Unsupported
ATT → CSA-adoption (H <sub>5</sub> )	-0.02	0.15	-0.34	0.734	Unsupported
SN → CSA-adoption (H <sub>6</sub> )	0.52***	0.06	7.52	0.000	Supported
PBC → CSA-adoption (H <sub>7</sub> )	0.20**	0.17	2.56	0.010	Supported

Note

\*\*\*, \*\*, and \* indicate statistical significance at 1%, 5% and 10%

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practices. Subsequently, behavioral intention, attitude, subjective norm, and perceived behavior control collectively explained a 30% variance in the adoption of CSA practices by smallholder farmers.

Standardized parameter estimates from the model are presented in Table 5 to show the different pathways. Subjective norm was revealed to have no significant effect on farmers' intention to adopt CSA practices hence, there was no evidence to support H<sub>2</sub>. Perceived behavior control was estimated to have a greater influence ( $\beta = 0.43$ ) than either attitude (0.25) or subjective norm ( $\beta = 0.02$ ) on farmers' intention to adopt CSA practices. Farmers' attitude was estimated to have a positive and significant effect ( $\beta = 0.25$ ,  $p < 0.000$ ) on farmers' intention to adopt CSA practices, providing evidence to support H<sub>1</sub>. The perceived behavior control of farmers was estimated to have a positive and significant ( $\beta = 0.43$ ,  $p < 0.000$ ) on farmers' intention to adopt CSA practices, thus supporting H<sub>3</sub>.

Table 5 shows that farmers' behavioral intention to adopt CSA practices played no mediating role on farmers' actual adoption of CSA practices. However, the subjective norm was estimated to have a positive and significant effect ( $\beta = 0.52$ ,  $p < 0.000$ ) on farmers' adoption of CSA practices, supporting H<sub>6</sub>. Perceived behavior control was estimated to have a direct positive and significant effect ( $\beta = 0.20$ ,  $p < 0.010$ ) on farmers' adoption of CSA practices, thus, supporting H<sub>7</sub>. Our results show that attitude and perceived behavior control positively affect farmers' intention to adopt CSA practices while subjective norm and perceived behavior control affect farmers' adoption of CSA practices.

#### 4.5. Discussion

Results from the SEM indicated that farmers' attitude has a positive and significant impact on farmers' intention to adopt CSA practices. A positive significant impact of attitude on farmers' intention implies that favorable opinions about CSA practices increases a farmer's chances of forming intentions to adopt such CSA practices. Forming such positive attitudes towards CSA practices depend on farmers' witnessing the positive impacts CSA practices have on farm output. Our results are consistent with the findings of previous studies [44, 67, 78, 79, 89] suggesting that attitude is the best starting point for behavioral change. Attitude is regarded as an important component in shaping farmers' intentions as it is the response to behavioral beliefs [42, 78, 90]. Farmers' attitude has been documented to significantly impact behavioral intention towards Conservation Agriculture [91]. Studies including [47, 92, 93] have indicated that attitude has the largest impact on farmers' behavior intention, however, our findings indicate the contrary and it is in line with the findings of [52] with attitude estimated to have a slightly negative impact on the actual adoption of CSA practices albeit insignificant. A possible

explanation for such negative impact of attitude on the adoption behavior of farmers is due to the minimal exposure of farmers to the actual results of CSA practices on farms that use an appropriate mix of CSA practices. [26] indicate that being close to a climate-smart village increases the likelihood of adopting climate-smart practices because farmers that have witnessed firsthand the results of CSA practices tend to develop a positive attitude toward such practices. The lack of a visible “success story” about the use of CSA practices casts doubts about the expected results and hence farmers are likely to develop a neutral or negative attitude towards CSA practices. This has implications for the adoption of CSA practices in farming communities in the study area where slight changes in rainfall can cause significant crop yield losses.

Perceived behavior control had a positive and significant effect on farmers’ intention to adopt CSA practices. By implication, the perception of farmers about their own capabilities to apply CSA practices significantly influences their behavioral intention and their subsequent adoption of such practices. Our results are consistent with the literature [44, 56, 91, 94], suggesting that higher perceived capability to apply CSA practices invariably leads to greater intention towards the application of CSA practices. The PBC component of the TPB suggests that, farmers who can overcome the different limitations in adopting CSA practices such as lack of information and resources will gain the motivation and develop the intention to adopt CSA practices [44, 95]. PBC was found to have a significant and positive effect on the actual usage of CSA practices. PBC had a significant and positive impact on CSA usage because farmers mostly want to feel in charge of their adoption behavior [67, 96]. This suggests that the perception of farmers about their capacity and degree of control over adoption significantly influences their intention and actual behavior [53]. However, studies such as [52] contend that PBC is not an important predictor of smallholder farmers’ intention to adopt production practices.

Subjective norm was found to have a significant and positive direct effect on CSA adoption. This suggests that farmers’ adoption behavior is influenced by perceived social pressure [56]. Social relations such as family members, neighbors, and opinion leaders play an active role in farmers’ adoption behavior. Subjective norm had the greatest effect on farmers’ adoption of CSA practices because farmers’ adoption decision is largely influenced by other’s opinion [92]. Social norm was found to have no significant effect on farmers’ intention to adopt CSA practices, this result is consistent with that of other studies such as [89, 97]. Although studies including [92, 93] have found subjective norm to significantly influence farmers’ intentions, their results revealed that social pressure/influence had extremely low impact on intentions relative to the attitude and perceived behavior control.

Contrary to the findings of [47, 96], our model indicated that behavioral intention plays no mediating role between attitude, subjective norm, perceived behavior control, and CSA adoption. The difference in the mediating role of behavioral intention may stem from constraints. This result implies that unanticipated events, insufficient time and resources, lack of requisite skills and several other factors may prevent farmers from acting on their intentions [98]. It is therefore important these constraints are addressed to enable farming communities to successfully implement appropriate CSA interventions aimed at moderating the adverse effects of climate change and variability on agro-based livelihoods.

It is important to stress that self-reported measures of behavior and intentions may differ from actual behavior and as such lead to no correlation between the measures [99]. The difficulty in accurately measuring the actual behavior of farmers has prevented researchers from going beyond just intentions. Our study contributes theoretically to this sparsely researched area by estimating actual behavior from past behavior. This is critical considering the projected increases in temperature and erratic rainfall partners across Ghana and West Africa more

widely. Findings from this study provides important information for policy makers to design climate change adaptation policy that take cognizance of the different psychological and behavioral factors that have the potential to influence the adoption of CSA practices.

## 5. Conclusion and policy implications

The study examined the different factors affecting smallholder farmers' intention to adopt and their adoption behavior towards CSA practices using a Structural Equation Model (SEM) based on the Theory of Planned Behavior (TPB). We have provided evidence of the extent to which the attitude, subjective norm, and perceived behavior control of smallholder farmers drive their intentions and subsequently their actual adoption of CSA practices in rural Ghana.

Findings showed that farmers' attitudes had a positive impact on farmers' intention to adopt CSA practices but had no direct impact on farmers' actual adoption behavior. This suggests that, the more positive attitudes farmers develop, the better the chances of increasing their intention to adopt CSA practices. Subjective norm had no impact on farmers' intention to adopt CSA practices but significantly impacted the actual adoption of CSA practices by farmers. The perceived influence from both internal and external sources had the largest impact on farmers' adoption behavior. Perceived behavior control had a significant impact on both farmers' intention to adopt and the actual adoption of CSA practices. That is, farmers' perception about their control over factors that could facilitate or hamper their adoption of CSA practices was the most significant driver of farmers' adoption of CSA practices in Ghana.

We recommend that more efforts should go into creating awareness among smallholder farmers to develop a more positive attitude towards CSA practices. Such positive attitudes by farmers towards CSA practices can be harnessed if demonstration fields of CSA practices are made available to demonstrate the positive effects CSA practices have on crop yields. The study recommends the need to create awareness of CSA practices by sharing that relevant information on CSA practices through community leaders including chief farmers, assembly members, clan heads, etc. so that such information can be easily passed on to farmers. Policy makers should encourage the establishment of demonstrating farms for farmers to appreciate the benefits associated with such practices.

## Supporting information

**S1 File. Sample questionnaire for data collection.**  
(DOCX)

**S1 Appendix.**  
(DOCX)

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## References

1. Atiah W. A., Amekudzi L. K., Akum R. A., Quansah E., Antwi-Agyei P., and Danuor S. K., (2021). "Climate variability and impacts on maize (*zea mays*) yield in Ghana, West Africa," *Quarterly Journal of the Royal Meteorological Society*, pp. 1–14, 2021.
2. Zimmermann A., Webber H., Zhao G., Ewert F., Kros J., Wolf J., et al. (2017). Climate change impacts on crop yields, land use and environment in response to crop sowing dates and thermal time requirements. *Agricultural Systems*, 157, 81–92.
3. Baffour-Ata F., Antwi-Agyei P., Apawu G. O., Nkiaka E., Amoah E. A., Akorli R., et al. (2021). Using traditional agroecological knowledge to adapt to climate change and variability in the Upper East Region of Ghana. *Environmental Challenges*, 4, 100205.
4. Tol R. S. (2020). The economic impacts of climate change. *Review of Environmental Economics and Policy*.
5. Bjornlund V., Bjornlund H., & Van Rooyen A. F. (2020). Why agricultural production in sub-Saharan Africa remains low compared to the rest of the world—a historical perspective. *International Journal of Water Resources Development*, 36(sup1), S20–S53.
6. Boko M., Niang I., Nyong A., Vogel C., Githeko A., Medany M., et al. (2007): Africa. In: Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Parry M.L., Canziani O.F., Palutikof J.P., van der Linden P.J., & Hanson C.E. (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA, pp. 433–467.
7. MoFA (2017). Agriculture in Ghana. Facts and Figures 2016 Statistics. Ministry of Food and Agriculture, Research and Information Directorate. Accra.
8. Asante F.A.; Amuakwa-Mensah F. (2015) Climate Change and Variability in Ghana: Stocktaking. *Climate*, 3, 78–99.
9. Abbam T., Johnson F. A., Dash J., & Padmadas S. S. (2018). Spatiotemporal variations in rainfall and temperature in Ghana over the twentieth century, 1900–2014. *Earth and Space Science*, 5(4), 120–132.
10. Environmental Protection Agency [EPA] (2011). Ghana Strategic Investment Framework (GSIF) For Sustainable Land Management (SLM) 2011–2025, Ministry of Environment, Science and Technology, Environmental Protection Agency, Accra, Ghana.
11. Dougill A.J.; Hermans T.D.G.; Eze S.; Antwi-Agyei P.; Sallu S.M. (2021). Evaluating Climate-Smart Agriculture as Route to Building Climate Resilience in African Food Systems. *Sustainability*, 13, 9909. <https://doi.org/10.3390/su13179909>
12. Lipper L., McCarthy N., Zilberman D., Asfaw S., & Branca G. (2014). *Climate smart agriculture: building resilience to climate change* (p. 630). Springer Nature.
13. Food and Agriculture Organisation. (2010). The state of food insecurity in the world 2010.
14. Boafo Y. A., Saito O., Kato S., Kamiyama C., Takeuchi K., & Nakahara M. (2016). The role of traditional ecological knowledge in ecosystem services management: the case of four rural communities in Northern Ghana. *International Journal of Biodiversity Science, Ecosystem Services & Management*, 12(1–2), 24–38.
15. Lipper L., & Zilberman D. (2018). A short history of the evolution of the climate smart agriculture approach and its links to climate change and sustainable agriculture debates. In: *Climate smart agriculture* (pp. 13–30). Springer, Cham.
16. Essegbe G. O., Nutsukpo D. K., Karbo N., & Zougmoré R. B. (2015). National climate-smart agriculture and food security action plan of Ghana (2016–2020). *CCAFS Working Paper*.

17. MoFA (2015). Medium Term Agricultural Sector Investment Plan (METASIP II). Ministry of Food and Agriculture, Accra.
18. Food and Agriculture Organisation. (2014). *The state of food and agriculture (SOFA) 2014*.
19. Zakaria A., Azumah S. B., Appiah-Twumasi M., & Dagunga G. (2020). Adoption of climate-smart agricultural practices among farm households in Ghana: The role of farmer participation in training programmes. *Technology in Society*, 63, 101338.
20. Antwi-Agyei P., Abalo E.M. Dougil A.J& Baffour-Ata F, (2022). Motivations, enablers and barriers to the adoption of climate smart agricultural practices by smallholder farmers: evidence from the transitional and savannah agroecological zones of Ghana. *Regional Sustainability*. Doi.org/10.1016/j.regsus.2022.01.005
21. Djido A., Segnon A. C., Botchway V. A., Karbo N., Sam K. O., Essegbe G. O., et al. (2021). Implementation, usage, and effectiveness of Ghana climate change policies: an assessment of the national CSA Action Plan and CSA Investment Framework. *CCAFS Info Note*.
22. Martey E., Etwire P. M., & Kuwornu J. K. (2020). Economic impacts of smallholder farmers' adoption of drought-tolerant maize varieties. *Land Use Policy*, 94, 104524.
23. Asfaw S., Di Battista F., & Lipper L. (2016). Agricultural technology adoption under climate change in the Sahel: Micro-evidence from Niger. *Journal of African Economies*, 25(5), 637–669.
24. Kassie M., Teklewold H., Jaleta M., Marenja P., & Erenstein O. (2015). Understanding the adoption of a portfolio of sustainable intensification practices in eastern and southern Africa. *Land use policy*, 42, 400–411.
25. Di Falco S., Veronesi M., & Yesuf M. (2011). Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *American Journal of Agricultural Economics*, 93(3), 829–846.
26. Tetteh B. K., Ansah I. G., Donkoh S. A., Appiah-Twumasi M., Avoronyo F. K., Shaibu M. T., et al. (2020). Perceptions of weather variability and climate change on goat producers' choice of coping and adaptation strategies: evidence from climate-smart and non-climate-smart villages in the Jirapa and Lawra districts. *Climate and Development*, 12(7), 614–625.
27. Sattler C., & Nagel U. J. (2010). Factors affecting farmers' acceptance of conservation measures—A case study from north-eastern Germany. *Land Use Policy*, 27(1), 70–77.
28. Schenck A., Hunziker M., & Kienast F. (2007). Factors influencing the acceptance of nature conservation measures—A qualitative study in Switzerland. *Journal of environmental management*, 83(1), 66–79. <https://doi.org/10.1016/j.jenvman.2006.01.010> PMID: 16621231
29. Meijer S. S., Catacutan D., Sileshi G. W., & Nieuwenhuis M. (2015). Tree planting by smallholder farmers in Malawi: Using the theory of planned behaviour to examine the relationship between attitudes and behaviour. *Journal of Environmental Psychology*, 43, 1–12.
30. Greiner R., & Gregg D. (2011). Farmers' intrinsic motivations, barriers to the adoption of conservation practices and effectiveness of policy instruments: Empirical evidence from northern Australia. *Land Use Policy*, 28(1), 257–265.
31. Dessart F. J., Barreiro-Hurlé J., & van Bavel R. (2019). Behavioural factors affecting the adoption of sustainable farming practices: a policy-oriented review. *European Review of Agricultural Economics*, 46(3), 417–471.
32. Foster A. D., & Rosenzweig M. R. (2010). Microeconomics of technology adoption. *Annu. Rev. Econ.*, 2(1), 395–424. <https://doi.org/10.1146/annurev.economics.102308.124433> PMID: 24386501
33. Ajzen I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, 50(2), 179–211.
34. Sok J., Borges J. R., Schmidt P., & Ajzen I. (2021). Farmer Behaviour as Reasoned Action: A Critical Review of Research with the Theory of Planned Behaviour. *Journal of Agricultural Economics*, 72(2), 388–412.
35. Ajzen I. (2015). Consumer attitudes and behavior: the theory of planned behavior applied to food consumption decisions. *Italian Review of Agricultural Economics*, 70(2), 121–138.
36. Steinmetz H., Knappstein M., Ajzen I., Schmidt P., Kabst R., (2016). How effective are behavior change interventions based on the theory of planned behavior? A three-level meta-analysis. *Zeitschrift für Psychologie* 224 (3), 216.
37. Trujillo-Barrera A., Pennings J. M., & Hofenk D. (2016). Understanding producers' motives for adopting sustainable practices: the role of expected rewards, risk perception and risk tolerance. *European Review of Agricultural Economics*, 43(3), 359–382.
38. Zhang Q., Xiao H., Duan M., Zhang X., & Yu Z. (2015). Farmers' attitudes towards the introduction of agri-environmental measures in agricultural infrastructure projects in China: Evidence from Beijing and Changsha. *Land Use Policy*, 49, 92–103.

39. Wachenheim C. J., Lesch W. C., & Dhingra N. (2014). The conservation reserve program: A literature review, Vol. 723. Agribusiness and Applied Economics Report, pp. 1–22.
40. Hyland J. J., Heanue K., McKillop J., & Micha E. (2018). Factors influencing dairy farmers' adoption of best management grazing practices. *Land Use Policy*, 78, 562–571.
41. de Lauwere C., van Asseldonk M., van't Riet J., de Hoop J., & ten Pierick E. (2012). Understanding farmers' decisions with regard to animal welfare: The case of changing to group housing for pregnant sows. *Livestock Science*, 143(2–3), 151–161.
42. Despotović J., Rodić V., & 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, 1196–1205.
43. Ajzen I. (2002). Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior 1. *Journal of Applied Social Psychology*, 32(4), 665–683.
44. Rezaei R., Safa L., Damalas C. A., & Ganjkhaneh M. M. (2019). Drivers of farmers' intention to use integrated pest management: Integrating theory of planned behavior and norm activation model. *Journal of Environmental Management*, 236, 328–339. <https://doi.org/10.1016/j.jenvman.2019.01.097> PMID: 30738304
45. Conner M., & Armitage C. J. (1998). Extending the theory of planned behavior: A review and avenues for further research. *Journal of applied social psychology*, 28(15), 1429–1464.
46. Ajzen I., & Schmidt P. (2020). Changing behavior using the theory of planned behavior. *The handbook of behavior change*, 17–31.
47. Dorce L. C., da Silva M. C., Mauad J. R. C., de Faria Domingues C. H., & Borges J. A. R. (2021). Extending the theory of planned behavior to understand consumer purchase behavior for organic vegetables in Brazil: The role of perceived health benefits, perceived sustainability benefits and perceived price. *Food Quality and Preference*, 91, 104191.
48. Scalco A., Noventa S., Sartori R., & Ceschi A. (2017). Predicting organic food consumption: A meta-analytic structural equation model based on the theory of planned behavior. *Appetite*, 112, 235–248. <https://doi.org/10.1016/j.appet.2017.02.007> PMID: 28188865
49. Ajzen I. (2011). The theory of planned behaviour: Reactions and reflections. *Psychology & health*, 26 (9), 1113–1127. <https://doi.org/10.1080/08870446.2011.613995> PMID: 21929476
50. Tan C. S., Ooi H. Y., & Goh Y. N. (2017). A moral extension of the theory of planned behavior to predict consumers' purchase intention for energy-efficient household appliances in Malaysia. *Energy Policy*, 107, 459–471.
51. Gao L., Wang S., Li J., & Li H. (2017). Application of the extended theory of planned behavior to understand individual's energy saving behavior in workplaces. *Resources, Conservation and Recycling*, 127, 107–113.
52. da Silva J. R., Mauad J. R. C., de Faria Domingues C. H., Marques S. C. C., & Borges J. A. R. (2020). Understanding the intention of smallholder farmers to adopt fish production. *Aquaculture Reports*, 17, 100308.
53. Vaz E. D., Gimenes R. M. T., & Borges J. A. R. (2020). Identifying socio-psychological constructs and beliefs underlying farmers' intention to adopt on-farm silos. *NJAS-Wageningen Journal of Life Sciences*, 92, 100322.
54. Li J., Zuo J., Cai H., & Zillante G. (2018). Construction waste reduction behavior of contractor employees: An extended theory of planned behavior model approach. *Journal of Cleaner Production*, 172, 1399–1408.
55. Rezaei R., Mianaji S., & Ganjloo A. (2018). Factors affecting farmers' intention to engage in on-farm food safety practices in Iran: Extending the theory of planned behavior. *Journal of Rural Studies*, 60, 152–166.
56. Tama R. A. Z., Ying L., Yu M., Hoque M. M., Adnan K. M., & Sarker S. A. (2021). Assessing farmers' intention towards conservation agriculture by using the Extended Theory of Planned Behavior. *Journal of Environmental Management*, 280, 111654. <https://doi.org/10.1016/j.jenvman.2020.111654> PMID: 33221044
57. Shin Y. H., & Hancer M. (2016). The role of attitude, subjective norm, perceived behavioral control, and moral norm in the intention to purchase local food products. *Journal of Foodservice Business Research*, 19(4), 338–351.
58. López-Mosquera N. (2016). Gender differences, theory of planned behavior and willingness to pay. *Journal of Environmental Psychology*, 45, 165–175.
59. Borges J. A. R., & Lansink A. G. O. (2016). Identifying psychological factors that determine cattle farmers' intention to use improved natural grassland. *Journal of Environmental Psychology*, 45, 89–96.

60. Daxini A., Ryan M., O'Donoghue C., Barnes A. P., & Buckley C. (2019). Using a typology to understand farmers' intentions towards following a nutrient management plan. *Resources, Conservation and Recycling*, 146, 280–290.
61. Läpple D., & Kelley H. (2013). Understanding the uptake of organic farming: Accounting for heterogeneities among Irish farmers. *Ecological Economics*, 88, 11–19.
62. Ajzen I. (1985). From intentions to actions: A theory of planned behavior. In *Action control* (pp. 11–39). Springer, Berlin, Heidelberg.
63. Wilson R. S., Schlea D. A., Boles C. M., & Redder T. M. (2018). Using models of farmer behavior to inform eutrophication policy in the Great Lakes. *Water research*, 139, 38–46. <https://doi.org/10.1016/j.watres.2018.03.065> PMID: 29626728
64. Zhang W., Wilson R. S., Burnett E., Irwin E. G., & Martin J. F. (2016). What motivates farmers to apply phosphorus at the "right" time? Survey evidence from the Western Lake Erie Basin. *Journal of Great Lakes Research*, 42(6), 1343–1356.
65. Chen M. F. (2017). Modeling an extended theory of planned behavior model to predict intention to take precautions to avoid consuming food with additives. *Food Quality and Preference*, 58, 24–33.
66. Sapp S. G., Harrod W. J., & Zhao L. (1994). Socially constructed subjective norms and subjective norm-behavior consistency. *Social Behavior and Personality: an international journal*, 22(1), 31–40.
67. Soorani F., & Ahmadvand M. (2019). Determinants of consumers' food management behavior: Applying and extending the theory of planned behavior. *Waste management*, 98, 151–159. <https://doi.org/10.1016/j.wasman.2019.08.025> PMID: 31446255
68. AL-Majali M. M., & Mat N. N. (2010). Applications of planned behavior theory on internet banking services adoption in Jordan: Structural equation modeling approach. *China-USA Business Review*, 9(12), 1.
69. Ghana Statistical Service (GSS). (2021). Ghana Population and Housing Census. General Report. Volume 3A.
70. Issaka Y. B., Antwi M., & Tawia G. (2016). A comparative analysis of productivity among organic and non-organic farms in the West Mamprusi District of Ghana. *Agriculture*, 6(2), 13.
71. Antwi-Agyei P., Stringer L. C., & Dougill A. J. (2014). Livelihood adaptations to climate variability: insights from farming households in Ghana. *Regional Environmental Change*, 14(4), 1615–1626.
72. Ghana Statistical Service (GSS), (2014). Ghana Living Standards Survey 6th Round: Poverty Profile in Ghana (2005–2013). Accra, Ghana.
73. Issahaku A. R., Campion B. B., & Edziyie R. (2016). Rainfall and temperature changes and variability in the Upper East Region of Ghana. *Earth and Space Science*, 3(8), 284–294.
74. Antwi-Agyei P., Fraser E. D., Dougill A. J., Stringer L. C., & Simelton E. (2012). Mapping the vulnerability of crop production to drought in Ghana using rainfall, yield and socioeconomic data. *Applied Geography*, 32(2), 324–334.
75. Taylor S., & Todd P. (1995). Decomposition and crossover effects in the theory of planned behavior: A study of consumer adoption intentions. *International journal of research in marketing*, 12(2), 137–155.
76. Shih Y. Y., & Fang K. (2004). The use of a decomposed theory of planned behavior to study Internet banking in Taiwan. *Internet research*.
77. Fishbein M., & Ajzen I. (2011). *Predicting and changing behavior: The reasoned action approach*. Psychology press.
78. Faisal M., Chunping X., Akhtar S., Raza M. H., Khan M. T. I., & Ajmal M. A. (2020). Modeling smallholder livestock herders' intentions to adopt climate smart practices: An extended theory of planned behavior. *Environmental Science and Pollution Research*, 27(31), 39105–39122. <https://doi.org/10.1007/s11356-020-09652-w> PMID: 32642898
79. Bagheri A., Bondori A., Allahyari M. S., & Damalas C. A. (2019). Modeling farmers' intention to use pesticides: An expanded version of the theory of planned behavior. *Journal of Environmental Management*, 248, 109291. <https://doi.org/10.1016/j.jenvman.2019.109291> PMID: 31352279
80. Kline R. B. (2011). Principles and practice of structural equation modeling (3 ed.). New York: The Guilford Press.
81. Hair J. F. Jr, Black W. C., Babin B. J., & Anderson R. E. (2010). Multivariate Data Analysis: A Global Perspective, 7th Edition. Pearson Education International.
82. Hair J. F., Black W. C., Babin B. J., & Anderson R. E. (2019). Multivariate Data Analysis, Eighth Edition.
83. Chin W. W. (1998). Commentary: Issues and opinion on structural equation modeling. *MIS quarterly*, vii–xvi.

84. Nasri W., & Charfeddine L. (2012). Factors affecting the adoption of Internet banking in Tunisia: An integration theory of acceptance model and theory of planned behavior. *The Journal of High Technology Management Research*, 23(1), 1–14.
85. Tanaka J. S. (1993). Multifaceted conceptions of fit in structural equation models. *Testing structural equation models*, 10–39.
86. Bentler P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin*, 107(2), 238. <https://doi.org/10.1037/0033-2909.107.2.238> PMID: 2320703
87. Hu L. T., & Bentler P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural equation modeling: a multidisciplinary journal*, 6(1), 1–55.
88. Bagozzi R. P., & Yi Y. (1989). On the use of structural equation models in experimental designs. *Journal of marketing Research*, 26(3), 271–284.
89. Menozzi D., Fioravanzzi M., & Donati M. (2015). Farmer's motivation to adopt sustainable agricultural practices. *Bio-based and Applied Economics*, 4(2), 125–147.
90. Senger I., Borges J. A. R., & Machado J. A. D. (2017). Using the theory of planned behavior to understand the intention of small farmers in diversifying their agricultural production. *Journal of Rural Studies*, 49, 32–40.
91. Bozorgparvar E., Yazdanpanah M., Forouzani M., & Khosravipour B. (2018). Cleaner and greener livestock production: Appraising producers' perceptions regarding renewable energy in Iran. *Journal of Cleaner Production*, 203, 769–776.
92. Lalani B., Dorward P., Holloway G., & Wauters E. (2016). Smallholder farmers' motivations for using Conservation Agriculture and the roles of yield, labour and soil fertility in decision making. *Agricultural Systems*, 146, 80–90.
93. Senger I., Borges J. A. R., & Machado J. A. D. (2017). Using structural equation modeling to identify the psychological factors influencing dairy farmers' intention to diversify agricultural production. *Livestock science*, 203, 97–105.
94. Borges J. A. R., de Faria Domingues C. H., Caldara F. R., da Rosa N. P., Senger I., & Guidolin D. G. F. (2019). Identifying the factors impacting on farmers' intention to adopt animal friendly practices. *Preventive veterinary medicine*, 170, 104718. <https://doi.org/10.1016/j.prevetmed.2019.104718> PMID: 31421489
95. Chen M. F. (2016). Extending the theory of planned behavior model to explain people's energy savings and carbon reduction behavioral intentions to mitigate climate change in Taiwan—moral obligation matters. *Journal of Cleaner Production*, 112, 1746–1753.
96. Strydom W. F. (2018). Applying the theory of planned behavior to recycling behavior in South Africa. *Recycling*, 3(3), 43.
97. Chen S. C., & Li S. H. (2010). Consumer adoption of e-service: Integrating technology readiness with the theory of planned behavior. *African Journal of Business Management*, 4(16), 3556–3563.
98. Ajzen I. (2020). The theory of planned behavior: Frequently asked questions. *Human Behavior and Emerging Technologies*, 2(4), 314–324.
99. Harland P., Staats H., & Wilke H. A. (1999). Explaining proenvironmental intention and behavior by personal norms and the Theory of Planned Behavior 1. *Journal of applied social psychology*, 29(12), 2505–2528.