



Research article

Do smallholder farmers belong to the same adopter category? An assessment of smallholder farmers innovation adopter categories in Ghana

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ABSTRACT

More often than not, good innovations introduced to farmers failed to be adopted or diffused among them, simply because the complexities and the variations in farmers' innovation adoption are not well explored. This study aims to analyse the innovation adopter categories that smallholder farmers belong to in Ghana and how their socio-economic attributes influence their innovativeness. A survey was employed to gather information from smallholder farmers in Ghana. The data obtained from the survey were analysed using the SPSS version 22 and the Individual Innovativeness (II) scales. The hypotheses were tested using the Logistic regression model. The results indicated a large number (36.6%) of the smallholder farmers belong to the late majority of the innovation adopter category. Also, more than three-quarters of the farmers were classified as low innovators. Factors such as farmer education and gender were found to be insignificant to their innovativeness, while other prominent factors were significant to farmers' innovativeness. The study also made a novel revelation on Roger's innovation adopter categorisation values. The study concluded that smallholder farmers in the study area do not belong to a homogenous innovation adopter category. Also, educated farmers without income are less innovative. It was therefore recommended that stakeholders introducing new technologies to smallholder farmers should develop attractive marketing packages combined with videos and pictures to educate farmers on the new products, to speed up adoption.

1. Introduction

Smallholder farmers' contribution to the world's food and nutrition security, sustainable rural economy, income and biodiversity equation cannot be underestimated. Globally, over 80 percent of the world's farms are operated by smallholder farmers (Ricciardi et al., 2018; Lowder et al., 2016; FAO, 2014), who operate on less than 2 ha of land (FAO, 2019). Smallholder farms are estimated to occupy less than 13 percent of the global arable lands; however, they provide close to 80 percent of the food produced in Asia and Sub-Saharan Africa (Fan and Rue, 2020; Awazi and Tchamba, 2019).

Smallholder farmers in Ghana comprise producers who farm on rain-fed lands outside their homestead, irrigated farmers, and farmers who produce crops and animals in their backyards or homestead gardens (Peprah et al., 2020; MoFA, 2006). They are characterised by using family labours, employing simple technologies and consuming significant parts of their produce (Hlophe-Ginindza and Mpandeli, 2020; Ennis and Renwick, 2017; Rapsomanikis, 2015). However, they produce close

to 90 percent of all farm produces in Ghana (Chamberlin, 2007; Nyan-teng and Seini, 2000). Their farms also serve as the primary source of raw materials and products for the rural enterprises (Teye and Torvikey, 2018; FAO, 2006). There is no doubt about the crucial roles that smallholder farmers play in the economy of Ghana; however, their innovation adoption is critical in ensuring a sustainable food supply.

The adoption of agricultural innovations, such as climate tolerance seed varieties, new disease-resistant breeds, and new machinery, can increase farmers' scale of production, food quality and quantity and help them cut down production costs through labour efficiency (Tomich et al., 2019). Smallholder farmers' innovation adoption contributes to both environmental and economic sustainability through the appropriate use of economic and environmental resources, such as water, land, and labour (FAO, 2018). And to a larger extent, the efficient use of these scarce resources can increase productivity at the farm level, which could contribute immensely to achieving the United Nations' Sustainable Development Goals (SDGs) 1, 2, and 12: ending food shortage, hidden hunger of nutritional deficiency, and poverty among farmers

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(FAO, 2018; Ayenew et al., 2018; Burchi et al., 2011). Yet, the social acceptance of innovation is crucial in this respect. Social acceptance of agricultural innovations, to some extent, depend on the structure and the functioning of the agricultural social system. Understanding the dynamics and the complexity of the elements within the social system will enable the execution of the appropriate methodological approaches to support the element within the system. The introduction of innovation to smallholder farmers is a complex process, owing to the fact that farmers are not in a homogenous group. Smallholder farmers vary in their demands, understanding, experience, and preferences; therefore, these farmers' complexity and heterogeneity should be prioritised (Fan and Rue, 2020; Rogers, 1995). Farmers' adoption of a new product depends on personal and social attributes and the necessity of the innovation (Olum et al., 2020; Kamrath et al., 2019; Rogers, 1995). The knowledge of the factors or adoption behaviour of farmers is vital to support the introduction of new strategies, products, or systems to enhance adoption (Roberts et al., 2021; Mottaleb, 2018).

Rogers (2003) established that the adoption and diffusion of new technologies in a social group such as smallholder farmers do not happen at the same time; some adopt earlier than others; therefore, different strategies are required at every level of the adopter category to get the innovation adopted.

It is bemoaned that many innovations introduced to farmers in Ghana face adoption and diffusion difficulties simply because the initiators of these innovations do not well understand the dynamism and the complexities among the potential adopters. Many a time, when new technologies are introduced to farmers, all the farmers are mistakenly considered to be on the same page of adoption; as a result, the same training and marketing strategies are provided to them without recognising the fact that farmers have varied characters, and that not all farmers adopt innovations in the same manner; nor are farmers' motivation the same in all settings (Molina-Maturano et al., 2021). Furthermore, most private companies tend to target resource-rich and educated farmers with new technologies more than the poor and uneducated farmers due to the perception that resource-rich and educated farmers are more innovative than poor and uneducated farmers. Unfortunately, this practice has caused many good technologies or innovations not to be adopted and diffused among farmers. However, Rogers (2003) stated that the individuals' perception of innovation has the largest impact on its rate of adoption and not the assumption of class attributed by experts or change agents. Meanwhile, past studies that attempted to explore the importance of socioeconomic variables on innovation adoption decisions obtained mixed results. Rogers (2003) described innovators under the adopter category as young, rich, and educated, implying that age, income, and education play a crucial role in innovation adoption. However, research by (Ullah et al., 2022; Staddon 2020; Mwangi and Kariuki, 2015) found no relationship between one or more of these socioeconomic variable (age, income, education) and innovation adoption. Also, other studies on innovation adoption focused on a segment of the adopter categories, as can be found in (Sääksjärvi and Hellén, 2019; Vainauskas, 2003; Agarwal et al., 1998); also on the adoption of agricultural technology in small-scale farming, on a broader perspective (Atriku, 2020), and on gender dimension of technology adoption (Quaye et al., 2021). At the moment, there has not been any research that has empirically analysed and classified smallholder farmers into innovation adoption categories in Ghana. Also, the main socioeconomic variables that influence smallholder farmers' innovativeness have not been explored fully. In light of the foregoing, the current study focuses more on the adopter categories of smallholder farmers in the Ketu North District of Ghana by analysing the innovation adopter categories that smallholder farmers belong to and how their socioeconomic attributes influence their innovativeness. This will pave the way for policymakers, agricultural advisors, marketers, and technology developers to plan and execute appropriate strategies that will help increase innovation adoption among smallholder farmers in the district and Ghana as a whole.

Specifically;

1. To group smallholder farmers into the various adopter categories
2. To determine smallholder farmers' innovativeness level
3. To analyse the basic socioeconomic attributes of smallholder farmers.

2. Literature review and theoretical framework

2.1. Diffusion of innovation theory

The hypotheses for the present study have their foundation in the Rogers diffusion of innovation theory. The theory analyses how members of a social system adopt innovation and how they make decisions towards its adoption. According to Rogers (2003), the adoption of innovations by individuals does not happen instantaneously; instead, on-time sequence. The degree to which an individual is relatively early in adopting innovation than others in a social system is called innovativeness (Rogers, 2003). Therefore, adopters were categorised based on their innovativeness. Rogers (2003) stated the differences between innovators and less innovators are linked to factors such as socioeconomic status, personality traits, and communication behaviour. Thus, social characteristics of innovators pointed them to be more educated, younger in age, higher in income, and so forth than others who adopt innovation later (Rogers, 2003; Jansson et al., 2011).

Education is considered one of the most important socioeconomic attributes that influence decision making in the human race. Education enables people to make informed decisions on issues and contribute constructively to decision making. While policymakers generally acknowledge that education plays a key role in economic development via the accumulation of human capital, it is also highly associated with boosting levels of social capital (Campbell, 2006). A study by Ruzzante et al. (2021) on the adoption of agricultural innovations in developing countries found educational levels to be positively correlated with farmers' adoption of many technologies. Similarly, Kabunga et al.'s (2017) research on dairy cows and nutrition improvement found a positive association between farmers' formal education and improved breed adoption. Moreover, other studies across Africa and Asia (Riddell and Song, 2017; Awotide et al., 2016; Uematsu and Mishra, 2010) have supported the view that formal education increases the adoption and use of technology among workers.

Conversely, Ullah et al. (2022) employed logistic regression to model farmers' innovation adoption decisions; they found education to negatively influence farmers' innovation adoption decisions in Pakistan. The importance of formal education on farmers' innovation adoption has given mixed results from past studies. We argue that the fact that a smallholder farmer is not educated does not make the person less innovative. Therefore, the first hypothesis for this study is;

H1. Formal education will not positively affect smallholder farmers' innovativeness.

Gender constitutes a great deal in men's and women's roles in most agrarian societies. Sociocultural values and practices in most developing countries sometimes prevent women from having a level playing ground with men. Access to resources, capital, and labour in many communities was reported to be under the control of men; thus, women's access to those scarce resources was subjected to the approval of men (Kristjanson et al., 2017; Goh, 2012). Although gender disparities have been considered higher in rural communities across Africa, this study argues that the fact that a farmer been a female or a male does not prevent him or her from becoming innovative. It is therefore hypothesised that;

H2. The gender of a smallholder farmer will have no positive impact on their innovativeness

Over the years, studies on age and innovation adoption in agriculture have given mixed evidence. Rogers (2003), in the innovation diffusion theory, categorised the last group (laggards) to adopt innovations as

characteristically older groups who show less interest in innovation adoption. Also, studies such as (Steinke et al., 2020; Aldosari et al., 2019; Challa and Tilahun, 2014) established an association between the age of farmers and technology innovativeness; young farmers were reported to adopt modern technologies for the same capital and labour level availability than older farmers (Mwangi and Kariuki, 2015). Similarly, the adoption of multiple technological innovations in farming was found to be higher among millennial farmers than among baby boomers (Ofori et al., 2020). Furthermore, in modern aquaculture farming, it was established that the level of understanding and changing of old methods was lower among older farmers than among younger farmers; moreover, technologies that were likely to produce results in the future were highly rejected by older farmers (Kumar et al., 2018).

Contrary to previous studies, older farmers are presumed to have gained knowledge and experience over time and are better positioned to evaluate and adopt technologies more than younger farmers (Mwangi and Kariuki, 2015). Similarly, Staddon (2020) found no relationship between age and technology adoption behaviour; the researcher concluded that young adults and older adults display similar attitudes towards digital technology use. We hypothesised that;

H3. The younger a farmer is, the more innovative they are likely to be.

Income is one of the major socioeconomic variables that is believed to influence one's purchasing power, access to community resources, participation in decision making, and marketing of goods and services (Fletcher and Wolfe, 2016). In the diffusion of innovation theory, Rogers characterised innovators as rich and possessing more capital than less innovators (Rogers, 2003). However, Davis (1993) theorised that individuals' decision to use a particular innovation is influenced by perceived usefulness and perceived ease of use (TAM). The researcher explained that when an individual senses that a particular innovation will enhance a job or a particular task, the person will go ahead and adopt such innovations. Also, when the person feels that the innovation will be easy to use for a particular task, they will adopt it (Liu et al., 2010). Davis' TAM theory implies that one's innovativeness or adoption of innovation is based on perceptions of beliefs one holds about the innovation. We believe that smallholder farmers' innovativeness is largely based on personal beliefs; therefore, the fourth hypothesis in the present study states that;

H4. Smallholder farmer's income will have no positive influence on their innovativeness

2.2. Concept of adopter categories

The innovation adoption curve developed by Rogers classifies users' entry into various categories based on their willingness to accept new technology or ideas. The curve follows a bell-shaped curve, and it is useful in segregating consumers into five different adopter categories as described below:

The innovators are the first in the adopter category of Rogers (2003). They are the first to adopt a new idea, technology or innovation. They are made up of a small percentage of the adopter population, almost 2.5 percent. Innovators are mostly young and have the highest social class. They are risk-takers by nature and get excited by the possibilities of new ideas. They are always eager to try new things, to the point where their venturesome almost becomes an obsession. Innovators' interest in new ideas leads them out of a local circle of peers and into more cosmopolitan social relationships than usual. They usually have substantial financial resources and the ability to understand and apply complex technical knowledge. Innovators also accept the occasional setback when new ideas prove unsuccessful (Rogers, 2003).

Early adopters are the second category of individuals who adopt innovation faster after innovators. They consist of about 13.5 percent of the total adopter population. They are the most influential people within any social system and often have a thought leadership (opinion leadership) for other potential adopters. Early adopters' approval of a new

product, idea or technology usually leads to market saturation. They are young in age, well-educated, have more financial lucidity, higher social status; they have a reasonable approach to risk and are more socially forward than other adopters; also, they are more discrete in adoption choices than innovators and do not want to be the last people to know about a product.

The early majority is a third group that appears in the adopter category. Statistically, they represent 34 percent of the adopter population. People in this category tend to be less affluent and less tech-savvy than early adopters. They are thoughtful and care about accepting new technologies; they are often called value shoppers. The early majority will adopt a new idea or product if they are confident that it will be valuable to them; they are risk-averse and always want to make sure that their scarce resources are spent wisely on valuable products. They mostly seek the opinion of the thought leaders (early adopters) when making adoption decisions on new products. They also rely on the recommendation of known people who have used the new products. Furthermore, they read reviews, articles, and brochures about the new product or technology to determine its usefulness. The early majority usually represent the first major wave of traffic for producers of the new product because 34 percent of potential adopters are in this category.

The late majority also represents 34% of the adoption population. Individuals in this category are older, less affluent, less educated, have less money, and a bit orthodox; they are sceptical about innovation and have below-average social status. They will only adopt an innovation after almost everyone has adopted it; they are only influenced by peer pressure. They are the group that will do thorough research about a new product and would want to see pictures or videos of people using the product before they will adopt it. In the late majority category, individuals often put their resources towards tried and tested solutions only and fail to take a risk.

Laggards are the last group in the Rogers' adopter category. They are the third highest population (16 percent) in the adoption category. They are adamant about change; they value traditional methods of doing things. They are reluctant to change. By the time laggards adopt the new technology, it might have already become obsolete. They are old, have the lowest social status; they are poor and show little to no opinion leadership; they only stay in touch with family and close friends. Laggards acceptance of a new product or technology is a sign of the product declining. They are not moved by peer pressure.

The diagram shows that only a few groups in the adopter category adopt innovation early; this group comprises 2.5 percent of the total population. The individuals who actually control the market of a new idea or product are the early majority and the late majority. Individuals in this group together form 68 percent of the total population. Members in this group have varied attitudes toward accepting new products, but their final acceptance of innovation leads to the market booming. On the other hand, Laggards are the third-highest adopter category; they form 16 percent of the adopter population. They are adamant about accepting innovations, but once they adapt, they become loyal and will not easily change for a different product.

2.3. Theory of the logistic regression model

Logistic regression is a form of linear regression model that uses a logistic function to model the probability of binary output variables. It models the likelihood of an observation, which is always bounded between 0 and 1 (Belyadi and Haghghat, 2021). The model aims to measure the relationship between a categorical dependent variable and one or more independent variables (mostly continuous) by plotting the dependent variables' likelihood scores (). Logistic regression is a suitable analysis model for classifying problems, where new sample suitability in a category is determined (Thomas et al., 2017). It is a classification model which is very easy to realise and achieves very good performance with linearly separable classes. It is an extensively employed algorithm for classification in the industry (Subasi, 2020). The fundamental difference

between linear and logistic regression is the range of bounded binary variables (0 and 1) used by logistic regression instead of linear regression's continuous variables. Also, due to the application of a nonlinear log transformation to the odds ratio, logistic regression does not make use of the linear relationship between input and output variables (Belyadi and Haghghat, 2021).

2.3.1. Assumptions of the logistic regression

1. The response variable is binary: the probability of an outcome occurring is the aim of logistic regression; therefore, predictions that are bounded between 0 and 1 are used.
2. The observations are independent.
3. There is a linear relationship between explanatory variables and the logit of the response variable.

The logistic regression model is believed to be developed and popularised primarily by Pierre François Verhulst, a Belgian Mathematician, in 1838 (Holypython, 2020). Since then, it has been adopted and used in bioassay and many other disciplines. More recently, it was used by Pearl of the U.S food administration to address the food needs of the growing population during World War I (Wilson et al., 2015). Similarly, Lowell of Johns Hopkins adopted the logistics curve for catalytic agents formed during a reaction (Holypython, 2020; Wilson et al., 2015).

2.3.2. Statistical model

Verhulst invented the logistic regression model for describing population growth. Verhulst gave a description function as;

$$Pt = \frac{e^{B_0 + B_1 t}}{1 + e^{B_0 + B_1 t}}$$

For the relation of proportion Pt as time increases. Let the linear relation be Logit [Pt] = $\beta_0 + \beta_1 t$, where β_0 denotes the value at time equal to zero, β_1 denotes the rate of change of logit [P_t] with regard to time and.

Logit [P_t] = log [pt/(1-P_t)]. The logistic function rises monotonically as t increases.

2.3.3. Limitations of the logistic regression model

The main limitation of logistic regression is that it can only be used to predict discrete functions. Thus, the dependent variable of Logistic Regression is restricted to the discrete set. This restriction is prohibitive to predicting continuous data (Al Shamali, 2015).

2.3.4. Importance of logistic regression

The logistic regression model is regarded as a sophisticated and well-developed model for analysing a binary response with a history of close to 100 years. It is appropriate for different kinds of data: prospective, cross-sectional, and retrospective analysis.

Its reliance on the odds makes it excellent for interpretation of the findings in the present study, as the results can easily be understood and related by different classes of people, especially in the field of agricultural and policy.

3. Materials and methods

The study was conducted in the Ketu North District of Ghana's Volta Region.

The study used questionnaires to obtain primary data from selected smallholder farmers. The research targeted smallholder farmers because they make up the majority of farmers in the study area.

3.1. Sample and sampling procedures

The selection of smallholder farmers was made based on the Ministry of Food and Agriculture's (2010) definition of a smallholder farmer; therefore, any farmer whose farm size was less than 3 ha was selected.

Firstly, three towns were selected from the district based on the concentration of farms and farmers. Secondly, the sample population was determined based on the total estimated population of farmers in the three towns selected. Thirdly, the probability proportionate to size sample procedure was used to select samples from each town (see Table 1), which gave a total of 145 smallholder farmers representing the same number of households as the sample size for the survey.

3.2. Data collection

Structured questionnaires were administered to the selected farmers. In a household where the respondent cannot read or does not understand the English language, an enumerator assists them by interpreting the questions to them, and then they indicate an answer to be chosen. Two weeks before the main questionnaire distribution, a pre-survey of 15 respondents was done to validate the questions and determine the average time spent on completing a questionnaire. During the pre-survey stage, the questions that looked too difficult for respondents to answer were modified.

3.3. Data analysis

To categorise the farmers into the correct adopter categories, the study adopted the Hurt et al. (1977) Innovativeness Scales. Hurt et al. (1977) developed the innovativeness scale as a short valid, and reliable Likert scale suitable for use in both self-administered questionnaires and face to face (personal) interviews. The scales measure individual degrees of innovativeness. It can be used before the innovation appears because it does not focus on the innovation, instead, the individual and how they behave. The scales have been used in many research and have shown strong psychometric characteristics. It has repeatedly demonstrated its usefulness as a valid measure of general innovativeness (Aldahdouh et al., 2019; Pallister and Fox, 1998). Twenty (20) items were generated; these items were written on the basis of the characteristics of the five innovative categories. The categories and a sample from each are as follows: innovator 'I consider myself adventuresome in a social system; early adopter, 'I consider myself as an opinion leader in a group I belong to; early majority, 'I make decisions deliberately and methodically; late majority, 'I like stability and consistency; laggard 'I am suspicious of new ideas. The questions were administered in a five-choice response format where respondents were instructed to give their level of agreement or disagreement with each of the twenty items on a scale of 1 (strongly disagree) to 5 (strongly agree). Scores were carefully assigned so that higher scores indicate a higher degree of innovativeness (see appendix for sample).

3.3.1. Calculation of adopter categories

Based on Hurt et al.'s (1977) Innovativeness Scales, the following computations were made to determine respondents' adopter categories:

That is; Adopter category (II) = 42 + TPA – TNA.

Where 42 is a constant value of the Hurt et al. (1977) Innovativeness Scales; TPA is Total Positive Attributes, and TNA is Total Negative Attributes.

Step 1 The scores for items 4, 6, 7, 10, 13, 15, 17, and 20 were summed up to obtain the Total Negative Attributes

Table 1. Sample population and sample selected.

| Town | No. of farmers | Sample size | Percentage |
|-----------|----------------|-------------|------------|
| Dzodze | 94 | 59 | 41 |
| Tadzewewu | 75 | 47 | 32 |
| Afife | 61 | 39 | 27 |
| Total | 230 | 145 | 100 |

- Step 2 The scores for items 1, 2, 3, 5, 8, 9, 11, 12, 14, 16, 18, and 19 were summed up to obtain the Total Positive Attributes (TPA).
- Step 3 A constant number (42) was added to the total score in Step 2, and then the total score obtained in Step 1 was subtracted from it to get the value for each respondent's adopter category.

Interpretation of scores:

- Scores above 80 are classified as Innovators.
- Scores between 69 and 80 are classified as Early Adopters.
- Scores between 57 and 68 are classified as Early Majority.
- Scores between 46 and 56 are classified as Late Majority.
- Scores below 46 are classified as Laggards/Traditionalists.

In general, people who score above 68 are considered highly innovative, and people who score below 64 are considered low in innovativeness.

NB: See appendix for the list of items.

In order to classify farmers into two main innovation groups (High innovative and Low innovative), their scores from the Hurt and co. Innovativeness Scales were grouped. According to Rogers' Innovation adopter grouping, the innovators and the early adopters combine to form the most innovative group in the category (Rogers, 2003). Therefore with the help of Hurt and co. Innovativeness Scales, all farmers who scored above 68 were classified as highly innovative, whereas those who scored below 68 were classified as low innovative.

3.3.2. Econometric model employed

To determine how the socioeconomic attributes of farmers impact their innovativeness, the logistic regression model was employed.

The binary logistic regression model is generally used to model cases containing binary responses (dichotomy variables). The model is a probabilistic model that explains the possibility that a respondent will be innovative or otherwise, considering a combination of factors. Many studies and research have successfully applied this model to predict farmers, consumers, and clients' adoption of new technologies, products, ideas, and behaviour changes. The noted ones among them are (Ling et al., 2021; Yurynets et al., 2019; Noorhosseini-Niyaki and Allahyari, 2012). Below is the description of the variables used in the study.

The logistic regression model was adopted because it combined categorical variables with dichotomous responses. The model is specified as follows:

The probability that a smallholder farmer will be highly innovative (belongs to innovative and early adopter categories) is represented by P_i :

$$Prob(Y_i = 1) = P_i = F(Q_i) = \frac{1}{1 + e^{-Q_i}} \tag{1}$$

while X_i represents the explanatory variables; α and β are the parameters to be estimated.

The probability that a smallholder farmer will not be highly innovative (not belonging to the innovative and early adopter category) is represented by $1 - P_i$; therefore Eq. (2) becomes;

$$Prob(Y_i = 1) = Prob(Y_i = 1) = (1 - P_i) = \frac{1}{1 + e^{-Q_i}} \tag{2}$$

From Eqs. (1) and (2), Eq. (3) can be formed

$$\frac{Prob(Y_i = 1)}{Prob(Y_i = 0)} = \frac{P_i}{1 - P_i} = e^{Q_i} \tag{3}$$

Where P_i is the probability that Y_i takes the value 1 and then $(1 - P_i)$ is the probability that Y_i is 0, and e is the exponential constant. Taking the log of Eq. (3) gives Eq. (4) as:

$$Q_i = \ln\left(\frac{P_i}{1 - P_i}\right) = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \dots + \beta_k X_{ki} + U_i \tag{4}$$

In this study, formal education refers to education received under the instruction of a trained teacher or instructor under the formal educational system. Therefore any education obtained from basic school to the university is considered formal education, whereas any other form of education outside the formal system is considered informal.

The interpretation of education in reference to years is:

0 = no formal education; 1–9 years = basic education; 10–12 years = secondary; 13–16 years = tertiary.

4. Results and discussions

4.1. The socioeconomic indicators of respondents

Table 3 gives a detailed account of the socioeconomic and demographic attributes of the respondents in this study. It can be observed that more than 60% of respondents were males while a little over 30% were females. This result suggests that males dominate agricultural activities in the study area. A similar result was observed by Oyekale (2021) and Asravor (2018) in their studies on farmers' risk adaptation behaviour. They concurrently found males to populate farming activities in Ghana and attributed it to the tediousness and the labour intensity of agricultural works in Ghana.

Furthermore, Table 3 reveals that 68% of the respondents were above 35 years while 32% were below 36 years. The observed result implies that only few youths are made up of the smallholder farmer population in Ghana. This result concord with Nyarko and Kozari's (2020) findings that youth in Ghana are neglecting the agricultural profession, leaving it in the hands of the aged. Similarly, a study by Zagata and Sutherland (2015) found that one-third of farms in the EU were owned by farmers above 65 years of age, while only a fraction (7.5%) were those below 35 years. The present findings indicate that ageing in the agricultural sector is taking a global trend, and therefore youth-centred agricultural policies and programmes are required to make the sector attractive to the youth.

Also, it can be observed that more than 75% of the respondents have received some form of formal education as against 24% who have never had any formal education (Table 3). Many of the respondents spent between one to nine years in school, while fewer of them spent between thirteen to sixteen years in school. The current result is astonishing because many researchers, notably (Bruce, 2015; Al-Hassan, 2008), have found and characterized smallholder farmers in Ghana to be highly illiterate; i.e., they can neither read nor write, even in their local languages. The reason for the differences in the present result and the other past studies could be linked to the study location. For instance, the present study was conducted in the Southern part of Ghana, whereas the studies by (Bruce, 2015; Al-Hassan, 2008) were conducted in the Northern part of Ghana. The southern Ghana (Volta region) is noted to have more educational facilities than the Northern part; this could therefore account for the higher number of educated respondents. Also explaining the differences between the present result and the former. However, having most smallholder farmers educated is welcoming news because they can read policy documents and make positive contributions to rural and agricultural policies. It will also influence their record-keeping and farm enterprise management skills positively.

Finally, the annual income of the respondents indicates that the majority of the respondents (81%) earn less than GHS5000, while less than one quarter (19%) earns above GHS5000. This result suggests that only few farmers earn a little above the minimum wage in Ghana. This could affirm the widespread view that many smallholder farmers in developing countries live in poverty (Hesselberg, 2017).

The results for the socioeconomic characteristics suggest that the district would not face difficulties implementing agricultural activities through digital platforms since the majority of the farmers are educated. However, affordability should be considered since many farmers earn less than GHS5000 annually.

4.2. Innovativeness and adopter grouping of smallholder farmers

Table 4 displays the score ranges obtained by the respondents and their adopter categories with their percentages. It could be seen that the least score range obtained by the respondents was 41–46, and the highest score range was 81–84, which represented 12.4% and 87.6%, respectively (Table 4). Also, most of the respondents (smallholder farmers) belong to the low innovative group, while fewer are found in the highly innovative group. This suggests that there are only a few smallholder farmers who are cosmopolitan, have higher social status, are eager to try new things, and have the ability to understand and apply complex technical knowledge in the study area. The present finding is inconsonant with Rogers's (2003) innovation adopter category grouping trend, where the highly innovative groups were less than the low innovative groups. However, in the present study, percentage differences were observed; cumulatively, 12.4% was obtained for high innovation against 16% in Rogers' grouping, and 87.6% for low innovation against 84% in Rogers' grouping. This means that although Rogers' concept of innovativeness classification may follow a similar trend, irrespective of the geographical area, the percentage values may vary based on several factors, such as the type of technology and the kind of people involved, among other things.

The study identifies smallholder farmers in the district understudy to be low in innovativeness; therefore, organisations and individuals who plan to introduce new technologies in the area should consider this so that the appropriate marketing strategies can be developed to speed up adoption.

4.3. Adopter categories of smallholder farmers

The classification of respondents into innovation adopters followed Rogers (2003) innovation adopter category (see Figure 1) procedure. From Figure 2, it can be seen that the innovators category was the least adopter category (1.4%) respondents belong to, followed by early adopters (11%), laggards (17.9%), early majority (33.1%), and the late majority (36.6%) respectively. Additionally, it can be observed that the early majority and late majority alone combined made up more than 60% of the total respondents. This implies that those in the early majority and the late majority categories are the main determiners of innovation adoption and diffusion in the Ketu North District.

Furthermore, in terms of dominant adopter category, Figure 2 shows that the late majority is the most prevalent category (36.6%) in the study region. This suggests that a number of smallholder farmers in Ghana, especially in the Ketu North District, are more sceptical about new technologies and may want to see pictures or videos of people using them before making adoption decisions or probably wait for about half of the population adopting them before they also decide to use them. Also, by comparison, the percentages obtained for each adopter category in the present study vary from the percentages of Roger adopter categories (see Figure 1). In the present study, we observed a trend of downwards reduction in innovativeness to an upwards increase

in less innovativeness. For instance, innovators are 1.4% in the current study as against 2.5% in Rogers and Laggards are 17.9% presently as against 16% in Rogers. Therefore, the obtained result suggests that a result from a macro level study (used by Rogers) may not show the same result at the micro-level (present study). i.e., Rogers' work was developed for the market (macro-scale), whereas the current study was developed for a category of farmers (micro-scale).

4.4. Analysis of adopter categories and socioeconomic indicators

Table 5 presents the logistic regression analysis results that test the four hypotheses on the effect of the predictor variables on the response variable. The main variables adapted in the model to predict the innovativeness of the respondents were educational level, age, gender, and income. The likelihood of the model to predict the outcome correctly was 89.7%, which indicates that the data fit the model.

It can be seen from Table 5 that the educational level of respondents has no significant influence on their innovativeness level. This implies that highly educated, less educated and uneducated farmers can be either innovative or less innovative. Contrary to this result, research by (Ruzzante et al., 2021; Bukchin and Kerret, 2020; Ntshangase et al., 2018) found farmer education to significantly influencing their innovativeness. The present finding does not downplay the importance of formal education in innovation adoption; however, it opens a debate that other factors also influence farmers' innovation decisions, and for that matter, education alone cannot be used as a basis to conclude that one farmer is more innovative than the other. The present result affirms the hypothesis that "Formal education will not have a positive effect on smallholder farmers' innovativeness."

Furthermore, respondents gender was found to be insignificantly associated with their innovativeness. i.e., a farmer being a male or a female cannot predict his or her innovativeness. Therefore, all things being equal, it would be incorrect for one to conclude that male farmers will adopt new ideas or innovations more than female farmers. These findings also agree with the second hypothesis, which states that "the gender of a smallholder farmer will have no positive impact on their innovativeness."

Additionally, the results in Table 5 show that the age of the respondents was significantly associated with their innovativeness. Age recorded a coefficient (B) of -2.232 and was significant at 0.001, which means that holding all factors constant, a unit increase in the age of respondents will cause a decrease in their innovativeness at an odds ratio of 0.107. The younger a smallholder farmer is, the more innovative they are than the older farmers. This result agrees with our third hypothesis. The present observation is consistent with Papadavid et al. (2017) study, who found younger farmers to be more diversified and engaged in eco-friendly agricultural practices more than older farmers in the EU. Considering the current findings and the age dynamics among farmers, as observed in Table 2, it will be important to implement attractive policies to attract more young people into farming to encourage new ideas and innovation adoption in the sector.

Finally, with respect to respondents' annual income, farmers who earn more annually (above GHS5000) are 6.563 times (Table 5) more

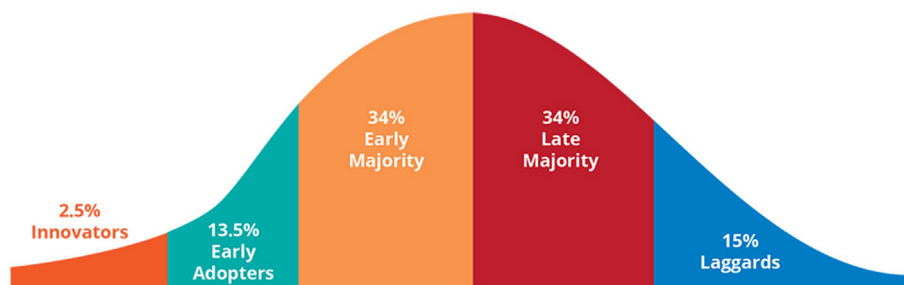


Figure 1. Adopter categorisation on the basis of innovativeness Rogers (2003).

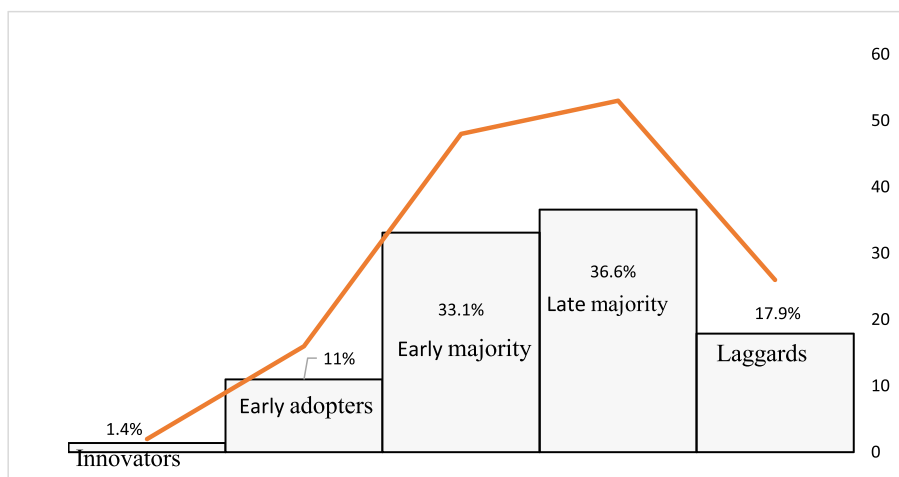


Figure 2. Adopter categories of smallholder farmers. Sources: Authors' survey, 2021

Table 2. Variables description.

| Variable | Coding | Expected sign. | Variable type |
|--------------------------|---|----------------|---------------|
| Innovativeness (Y_1) | 0 = low innovative 1 = high innovative | | dependent |
| Education | Years of schooling | + or - | independent |
| Age | Age in years | + or - | independent |
| Gender | 0 = male; 1 = female | + or - | independent |
| Income | 0 = below GHS 5000 1 = Above GHS5000 | + or - | independent |

Table 3. Socioeconomic indicators of respondents.

| Variables | Frequency | Percentages |
|--------------------------|-----------|-------------|
| Gender | | |
| Male | 94 | 65 |
| Female | 51 | 35 |
| Age | | |
| Below 36 yrs. | 46 | 32 |
| Above 35 yrs. | 99 | 68 |
| Educational level | | |
| No formal education | 35 | 24 |
| Basic education | 87 | 60 |
| Secondary | 17 | 12 |
| Tertiary | 6 | 4 |
| Annual Income | | |
| Below GHS 5000 | 117 | 81 |
| Above GHS 5000 | 28 | 19 |

Sources: Authors' survey, 2021. $GHS1 = 0.17\$$.

Table 4. Innovativeness and adopter grouping of smallholder farmers.

| Score range | Category | Innovative type | Percentage |
|-------------|----------------|-----------------|------------|
| 81–84 | Innovators | High innovative | 12.4 |
| 69–76 | Early adopters | | |
| 57–67 | Early majority | Low innovative | 87.6 |
| 46–56 | Late majority | | |
| 41–46 | Laggards | | |

Sources: Authors' survey, 2021

Table 5. Analysis of adopter categories and socioeconomic indicators.

| Variables | Coefficients (B) | Standard error | Sig. | Odd ratio |
|-----------------------------|------------------|----------------|-------|-----------|
| Education | 1.444 | 1.141 | 0.206 | 4.238 |
| Age | -2.552 | 0.705 | 0.000 | 0.078 |
| Gender | -1.353 | 0.816 | 0.097 | 0.259 |
| Income | 1.881 | 0.684 | 0.006 | 6.563 |
| Constant | 0.062 | 2.113 | 0.977 | 1.064 |
| Model Summary | | | | |
| | χ | DF | sig. | |
| Goodness-of-fit test | | | | |
| -2 Likelihood test | 77.956 | 4 | 0.000 | |
| Chi-square test | 30.820 | | | |
| Nagelkerke R^2 | 0.363 | | | |
| Total variable | 145 | | | |
| Correct prediction | 89.7% | | | |

likely to be highly innovative than farmers who earn less (less than GHS5000) annually, holding all factors constant. This implies that increased income increases innovativeness among smallholder farmers. The obtained result is plausible because higher income increases farmers' purchasing power, builds their confidence, and also makes them take higher risks. A study by Gajewski et al. (2022) found an association between multiple incomes and risk-taking; they observed that a 1% increase in temporary income corresponded to a 12.7% risk-taking. Moreover, new technologies are known to be a bit pricey, as such, farmers with higher incomes are likely to afford them more than farmers with lower incomes. A study by Diiro and Sam (2015) found that farmers in Uganda who earned higher income and had more assets applied new technologies (seed varieties) on their farms more than farmers whose incomes were lower. Similarly, Bukchin and Kerret (2020) found that higher annual income increased farmers' drip irrigation adoption. The finding from this study, therefore, adds to the academic debate that higher annual income of farmers directly increases their innovativeness; hence, our results in Table 3, showing a higher number of smallholder farmers with lower annual income, could explain why many smallholder farmers are less innovative (see Table 4 and Figure 2). The present result does not agree with the fourth hypothesis in this study; it is therefore rejected.

5. Conclusions and recommendations

The current study aims to analyse the innovation adopter categories that smallholder farmers belong to in the Ketu North District of Ghana, and how their socioeconomic attributes influence

their innovativeness. The study concludes that smallholder farmers belong to different innovation adopter categories; however, the late majority adopter category was the most dominant adopter category that majority of the smallholder farmers belong to in the Ketu North District of Ghana.

Also, the study identified the educational status and gender of the smallholder farmers to have no significant influence on their innovativeness; that is, one cannot use the gender or educational status of farmers to predict their innovativeness. Instead, farmers' age and income significantly influence their innovativeness. That is, younger smallholder farmers were more technophilia and innovative compared to the older smallholder farmers. Additionally, smallholder farmers with high annual income were more innovative than smallholder farmers with low annual income. The study therefore made a proposition that educated smallholder farmers without income are less innovative.

Also, the present study has found an interesting trend in the farming sector in the study area; the younger smallholder farmers were fewer than the older smallholder farmers, this resulted in increasing number of less innovative smallholder farmers (belong to the early majority, late majority and laggards categories) in the district. Furthermore, the study has made a new revelation by establishing that Rogers' innovation adopter category percentages are not constant; they are subject to change based on the type of innovation, technology, and the characteristics of the social system under study.

The study accepted the first three hypotheses stated in this study and rejected the fourth hypothesis; stating that "Smallholder farmers income will have no positive influence on their innovativeness".

The scientific evidences from the present study provide important benchmark for future studies into farmer innovation adoption. It has also made an important revelation on Rogers's adopter category graph, opening an interesting debate for further inquiries. This study has empirically affirmed some of the theoretical arguments raised in the literature on innovation adoption and adopter categories. The understanding of farmers' innovativeness level and the possible factors that influence them are critical in the era of technological advancement, as it may help in planning and executing programmes that have the potential to enhance new technologies adoption and utilisation among smallholder farmers in Ghana and beyond.

Based on the findings from the study, the following recommendations proposed:

Agricultural policies that target the youth in rural areas should be implemented to attract youth in rural areas into farming. A Special subsidy programme targeting youth in farming should be implemented. Irrigation schemes can also be implemented in the area to enable farmers produce throughout the year without water difficulties; this will motivate them to adopt new breeds of seeds and farm implements.

Integrated local economic growth should be prioritised. This will increase the utilisation of local products. In return, farm income will increase through purchasing of farm produce, which will also lead to farms expansion and producing more to feed local industries and people.

Furthermore, stakeholders introducing new technologies to smallholder farmers should develop attractive marketing packages combined with videos and pictures to educate farmers on the new products, this will help speed up their adoption. We also recommend that future study examines the hypothesis generated from the present study: educated farmers without income are less innovative.

Moreover, a replication of the study by increasing the sample size to cover other smallholder farmers and commercial farmers in a macro-region is proposed.

Also, future studies could include other variables such as land size, family size, access to government subsidies, and informal education (training, seminars) to model their impact on farmers' innovativeness.

Finally, to broaden the understanding and applicability of variables, future studies could adopt the Structural equation modelling (SEM) to model the relationship the factors used in the study have on farmers' innovativeness.

Declarations

Author contribution statement

Daniel Nyarko Ayisi: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

József Kozári, Tóth Krisztina: Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Data availability statement

Data will be made available on request.

Declaration of interest's statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

Appendix

Directions: People respond to their environment in different ways. The statements below refer to some of the ways people can respond. Please indicate the degree to which each statement applies to you by marking whether you: Strongly Disagree = 1; Disagree = 2; are Neutral = 3; Agree = 4; Strongly Agree = 5 Please work quickly, there are no right or wrong answers, just record your first impression.

1. My peers often ask me for advice or information.
2. I enjoy trying new ideas.
3. I seek out new ways to do things.
4. I am generally cautious about accepting new ideas.
5. I frequently improvise methods for solving a problem when an answer is not apparent.
6. I am suspicious of new inventions and new ways of thinking.
7. I rarely trust new ideas until I can see whether the vast majority of people around me accept them.
8. I feel that I am an influential member of my peer group.
9. I consider myself to be creative and original in my thinking and behavior.
10. I am aware that I am usually one of the last people in my group to accept something new.
11. I am an inventive kind of person.
12. I enjoy taking part in the leadership responsibilities of the group I belong to.
13. I am reluctant about adopting new ways of doing things until I see them working for people around me.
14. I find it stimulating to be original in my thinking and behavior.
15. I tend to feel that the old way of living and doing things is the best way.
16. I am challenged by ambiguities and unsolved problems.
17. I must see other people using new innovations before I will consider them.
18. I am receptive to new ideas.
19. I am challenged by unanswered questions.
20. I often find myself skeptical of new ideas.

Scoring:

- Step 1: Add the scores for items 4, 6, 7, 10, 13, 15, 17, and 20.
 Step 2: Add the scores for items 1, 2, 3, 5, 8, 9, 11, 12, 14, 16, 18, and 19.
 Step 3: Complete the following formula: $II = 42 + \text{total score for Step 2} - \text{total score for Step 1}$.
 Scores above 80 are classified as Innovators.
 Scores between 69 and 80 are classified as Early Adopters.
 Scores between 57 and 68 are classified as Early Majority.
 Scores between 46 and 56 are classified as Late Majority.
 Scores below 46 are classified as Laggards/Traditionalists.
 In general people who score above 68 and considered highly innovative, and people who score below 64 are considered low in innovativeness.

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