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Social networking and risk attitudes nexus: implication for technology adoption among smallholder cassava farmers in Ghana

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Abstract

Background: Theoretically, social climate and social networking which may affect attitudes, motivations, and readiness towards quality improvement and rewards, influence the adoption decision process by possibly modifying the risk behaviour/attitudes of individuals. Thus for effective promotion of agricultural technologies among farmers in Africa, it is necessary to understand the social context within which risk attitudes are formed and social participation decisions are made. The study, therefore, employed the recursive bivariate endogenous switching probit model to examine how risk attitudes of farmers are shaped through social interactions in the information and communication networks of farmers to influence their technology adoption decisions. Here, the empirical application was done with the contextual case of agriculture intensification technologies in the Root and Tuber Improvement and Marketing Programme (RTIMP) introduced to smallholder cassava farmers in Ghana. This paper makes a contribution to recent advances in the empirical analysis of impact where anticipated problems posed by unobserved confounders are accounted for. This was possible since the approach used allows for the estimation of the treatment effect of endogenous risk attitude variable of interest on farmers' adoption decisions.

Results: The study found that the effectiveness and usefulness of social interactions as well as a high degree of trust by cassava farmers in their social networks have higher tendencies to lower the degree of risk aversion behaviour of the farmers to significantly influence RTIMP Technologies adoption decisions positively. The ATE estimate confirms that there has been a significant increase of 38% probability in the likelihood of adopting agricultural intensification technologies in the RTIMP attributable to the non-risk aversion attitudes of cassava farmers. The cassava farmers' risk attitudes were found to be significantly influenced by the effectiveness and usefulness of social interactions, and a high degree of trust as well as age, frequency of extension services, access to credit, and revenue.

Conclusion: By implication, attempts to introduce innovations to improve agricultural commodities value chains that target farmers must pay particular attention to the information and communication network to ensure the effectiveness and usefulness of information dissemination to farmers in an honest manner, so as to build trust; which will go a long way to reduce doubts and uncertainties (function of risk aversion). This will help achieve higher innovation adoption impacts thereby resulting in attaining the overall deliverable objectives of agricultural innovations.

Keywords: Risk aversion, Social interactions, Technology adoption, Cassava, Smallholder farmers, Recursive bivariate probit, Ghana

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Introduction

Globally, root and tuber crops such as cassava, yam, sweet potatoes, and cocoyam are important food security and poverty alleviation crops, especially in most developing economies [51]. As food staples, cassava, yam, cocoyam, and taro, according to Ferraro et al. [32], are grown for the purpose of meeting food security and nutrition needs, and business opportunity gaps for over two billion people globally. In Ghana, the root and tuber crops are the most important food crops for direct human consumption, with an aggregate value of cassava, yam, and cocoyam of 30,208,643 MT exceeding all other Ghanaian staples, including cereal and plantain crops [65]. The cassava value chain is a food crop sector in Africa with great potential in terms of improving productivity, ensuring value-added, and developing regional trade due to the huge socio-economic benefits it renders to a large section of the populace. As a food staple for the majority of the people, improving the cassava value chain provides strategic products that can positively contribute to Sustainable Development Goals (SDGs) 1 and 2. SDG 1 emphasizes reducing poverty whiles SDG 2 targets achieving food security and improved nutrition through the promotion of sustainable agriculture to end hunger and famine [47, 90]. With an improved cassava value chain, the incomes of farmers and other actors along the chain will be improved to contribute to poverty reduction whiles making available sufficient wholesome cassava food products worthy of consumption. In an effort to enhance food security and income of poor rural households in Ghana, the Government of Ghana in collaboration with IFAD 2007, initiated the Root and Tuber Improvement and Marketing Programme (RTIMP) [51, 66]. In Ghana, RTIMP technologies were introduced to transform the root and tuber value chain into a more vibrant and competitive market-based commodity chain to enhance the livelihood of the rural poor [67, 79]. The focus of RTIMP was to develop Ghana's agricultural commodity chain for root and tuber crops. Technically, the programme was aimed at enhancing, developing a competitive market base, and promoting root and tuber products [79].

Additionally, the programme was to support the competitive market-based Root and Tuber Commodity Chain with relevant, effective, and sustainable services, and this was to be available to the rural poor [48, 67]. The RTIMP thus supports the development of several root and tuber commodities (cassava, yam, cocoyam, and sweet potato) value chains in the country. This saw the creation of chain facilitation linkages. The RTIMP Chain Facilitation focused on four (4) key chains: The fresh Yam chain, the Gari chain, the High-Quality Cassava Flour Chain, and Bonding cassava flour for the plywood industry. Notable among them is the cassava flour as glue extender for plywood manufacture (Cassava plywood chain). It thus becomes obvious how improving the cassava value chain was a critical must and thus the study focus. To achieve the objective of RTIMP, the programme adopted a farmer participatory approach to disseminating improved technologies on the root and tuber value chain to rural farmers [48, 67, 75]. As food security and poverty alleviation programme, its success and sustainability centred much on the willingness of farmers to fully adopt and utilize the innovations. In the RTIMP, cassava farmers were introduced to technologies under the following components: land preparation technology, improved planting material (high-yielding varieties), planting technology, and improved cultural practices. The study aims at investigating farmers' adoption of these sustainable intensification technologies as packaged in the RTIMP (dubbed RTIMP_Technologies in the context of the study). In order to speed up the adoption process and efficient utilization of technologies in RTIMP, several studies have been conducted to investigate the determinants of the adoption of RTIMP, by focusing on crop-specific technologies.

As a key implementation outcome, the adoption of innovations is a complex, multi-faceted decision-making process [78, 77, 97]. It is noted that the sustainability of any innovation, rests on the adoption and utilization of the various technologies associated with the innovation [14, 28, 69]. Hence understanding the adoption process may provide valuable insights for the development of strategies to facilitate effective uptake of Evidence Based Practices (EBPs) [97]. It has been reported that the successful adoption and utilization of any agricultural technology by farmers, to a large extent, depends on their decision-making and behavioural change process, as well as the risks and uncertainties associated with the said technology [16],Yu and Cao 2014.

In the Advanced Conceptual Model of Evidence Based Practice (EBP) implementation [1] as well as the theoretical framework by Wisdom et al. [97], about 27 predictors critical for the adoption of innovations are organized in four contextual levels (see [1, 97]). The four contextual levels critical for adoption are the external system, organization, innovation, and individual. Across these levels are a range of predictors key among them are social interactions and risk behaviour of supposed beneficiaries of innovation technology for adoption. Traditionally, the adoption of new technology by farmers is often clouded with much unpredictability due to the uncertainty surrounding the expected outcome associated with the use of the technology. Researchers have, therefore, argued that although new agricultural technologies aim at reducing risk in agricultural production, it is expected that the variation in the risk attitude of farmers may influence the adoption rate of any profitable agricultural technology [69, 87, 100]. Thus, an understanding of farmer-risk attitudes is key to finding ways to increase the adoption rate of RTIMP by root and tuber crop farmers in Ghana.

Again, experience gain through social interaction can also play a crucial role in the adoption decision process of farmers [42, 62, 83, 102, 102]. Monge et al. [68] have emphasized that people's behaviour is determined in part by their embeddedness in the social network; accordingly experience gained through learning from other social actors helps in shapening risk behaviour and decision to adopt agricultural innovations [83]. By implication, social interactions become a vital source of information in the diffusion of agricultural innovations. To speed up the diffusion of new technology, the nature and degree of social interaction among farmers are paramount. For instance, it is generally agreed among researchers that, social interaction forms the basic unit in any social system and that it has strong effects on the diffusion of agricultural technologies and their subsequent adoption and effective utilization [37, 63, 83].

Strong conceptual arguments have been that social climate and social networking (interactive learning space) may give experience and affect attitudes, motivations, and readiness towards quality improvement and rewards to influence the adoption decision process by possibly modifying the risk behaviour/attitudes of individuals. This notwithstanding, many of the empirical studies seeking to understand the adoption decision process have rarely given attention to investigating this vital connection to explaining the adoption decisions of farmers. The literature review found few studies which were conducted outside sub-Saharan Africa that have investigated social interactions and risk attitudes of farmers and their decision to adopt new technologies (see [42, 62, 89, 102, 102]. Risk attitudes and social interaction form the basic unit of the individual decision-making process in relation to the adoption and usage of new technologies [42, 62, 92, 100]. Despite the central role these variables might play as key predictors of technology adoption, studies on the adoption of agriculture intensification technologies in the RTIMP (RTIMP_Technologies) in Ghana have rarely considered how both variables interact to influence cassava farmers' adoption decisions. The current paper aims to contribute to filling this research gap. This paper also makes a contribution by applying of empirical estimation approach following recent advances such as [34, 40, 49, 53, 61] in econometrics for analysing the impact. Here, anticipated problems posed by unobserved confounders are accounted for. This is because the approach used allows for the estimation of the treatment effect of endogenous risk attitude variable of interest on farmers' adoption decisions.

The paper proceeds as follows: the next section discusses the theoretical framework based on which the study was conceptualized followed by how data for the study were obtained in a survey. This is then followed by the section on the empirical framework for the analytical measurement and modelling of study variables and further, results and discussion. The last section of the paper presents conclusions and policy implications from the study findings.

Theoretical framework

In the framework of the design and analysis for the study, three exclusive behavioural theories that are critical in the understanding of the adoption decision process of farmers are used. The theories explain social interaction, risk and adoption of technologies as follows. The current study have been designed to explore/examine the empirical connect between the three main constructs (variables) that could be empirically measured/estimated based on their theoretical explanations from the literature.

Theoretical underpinnings of social interaction

Generally, social scientists hold verified opinion on the meaning and content of social interaction, however, as suggested by Scheinkman, social interaction defines a particular form of externalities, in which the actions of a reference group affect an individual's preferences [84]. Intuitively, because social interactions are not regulated by the price mechanism, economist treat it as a non-market interactions. Scholars have emphasized that, farmer's behaviour is determined in part by their embeddedness in social networks, which to an appreciable extent enable farmers to learn the best ways of applying new and improved technology and to judge their usefulness and effects Rogers [80]; [68]. In practice, models of social interactions suggests that individuals response to social stimuli when they perceive that the marginal utility to be derive from undertaking an action increases with the average amount of the action taken by his neighbours (Scheinkman 2008). This by implication suggests that, there is a bi-directional change effects, which can be direct or indirect. Here, individuals do not only response to social stimuli because of the fundamental direct change, but also because of the change in the behaviour of the members of the same social group.

As noted by Maertens and Barrett [56], theoretical models of social interaction that has been applied in agricultural research assumes that farmers learn by observing others' experimentation, thus, to have a comprehensive path analysis of social interaction, one must focus on the following key dimensions: (i) what do farmers value and over what time period? (ii) what type of information does the farmer absorb and from whom? (iii) how does the farmer learn or update his belief? (iv) how do beliefs translate into actions? (v) do agents interact strategically? Answers to these help to analyse the path and effects of social interaction among social groups.

Another theoretical underpinning of social interaction is that, farmers' engagement in social interaction provides them with new technological knowledge and that they weigh each piece of information proportionately to its value [24]. In principle, social interaction is seen as source of information gathering among social groups. For instance, as noted by Foster and Rosezweig [36] farmers are able to gather information concerning agricultural technology through two main approaches. That is, learning by doing and learning from others. Technically, learning by doing reflects a situation where by a farmer gains experience and updates beliefs from using the technology over time. This emphasizes an internal learning process through self-experimenting with the technology. On the other hand, learning from others places more emphasizes on external information from the influences of social interactions, by observing peers. As noted by Henslin, in sociological perspective, analysis of social interaction is a microsociological approach to understanding how interaction among social groups affects the behaviour of the individual members. This microsociological approach places emphasis on face-to-face social interaction, or what people do in response to action of peers [45]. Additionally, studies have suggested that to have a comprehensive perspective of the effects of social interaction on individual's behaviour should focus on certain key dimensions such as the frequency of interaction, perceived usefulness of the interaction, perceived effectiveness of the interaction, how individual trust information, among others [68], Abadi et al. [2]. Furthermore in the context of technology adoption, in analysing the effect of social interaction, two dimensions are often relevant: learning about the parameters of technology from and learning about its profitability [17]. In summary, social interaction analysis is a sociological perspective which tries to understand how the behaviour of individual depends on the actions or in actions of people with similar characteristics in the social system.

Theoretical underpinnings of farmers decision-making under risk

Farmers like all other producers make decision every day that affects their production ventures. The uncertainty associated with the outcomes from agricultural production, present farmers with risky situation. Consequently, farmers make decision in line with the objective of utility maximization. If the utility associated with the choice of taking a particular decision outweighs that of not taking that action, the farmer would opt for that option or otherwise. Theoretically, farmers' responses to risky prospects defines their risk attitudes. Based on their risk attitudes, farmers can be group into three categories: risk-averse, risk-loving and risk-neutral. Risk-averse are those who try to avoid taking risks; risk-lovers those who are open to more risky business options; and risk-neutral farmers are indifferent to risky prospect. As noted by Xu et al. [99] farmer-risk attitudes, as well as their empirical measurement have been an on-going concern for agricultural economists. Fundamentally, economic research into individual risk attitudes has it foundation from a set of behavioural axioms proposed by von Neumann and Morgenstern [72] and subsequently developed by Pratt [76] and Arrow [13], Tversky and Kahneman [93], among others. Intuitively, the identification and categorization of farmers' risk attitudes is of theoretical and practical importance, in the context of agricultural production.

Empirically, researchers have employed various utility maximization functions to estimate the risk attitudes of farmers. Some of these methods include the discounted utility model, expected utility model, rank dependent utility model, and cumulative prospect theory, among others. Following Moscardi and de Janvry [70] the various approach used to elicit the risk attitudes can be grouped into two: (1) the direct approach, based on the von Neumann–Morgenstern model and (2) the indirect approach. The authors argued that the direct model, developed by von Neumann and Morgenstern, has serious difficulties stemming from the fact that the decision-makers have different level of tolerance or intolerance for risky prospects and that the concepts of probability are by no means intuitively evident [91]. Although, several criticism have been raised against the Neumann and Morgenstern (N-M) Expected Utility (EU), others however, have suggested that the expected utility theory of von Neumann and Morgenstern is still a powerful tool for analysing individual decision-making under risk [85, 11, 12]. One argument that has been raised in line with the apparent violations of the EU model in studies designed to test its predictive power, is that the violation occurred because improper account is taken of the costs and benefits associated with the decision-maker's choice (Anderson et al. 1985). Anderson et al. [11, 12] in support of the position by Schoemaker [85], argued that, despite the various criticism that have been raised against the EU model, the model stills remains a good empirical approximation to reality. Now to account for the deficiency realized in the N-M model, Anderson et al. developed a modified version of the N-M model referred to as the Equally Likely Certainty Equivalent (ELCE). The ELCE model is designed to avoid bias caused by probability preferences through the use of ethically neutral probability [91]. Anderson et al. [12], further argued that using the ELCE approach makes the EU model the simplest but efficient operational framework for eliciting risk in agriculture. The ELCE since it was propounded, has seen growing application in the field of agricultural economic research.

Furthermore, it has been suggested that the use of simpler but intuitive measures of risk attitude with computational flexibility is useful for eliciting the risk attitudes of farmers [99, 101]. In line with this, agricultural economists have found the Equally Likely Certainty Equivalent (ELCE) estimation approaches as the most common and efficient approach to elicit farmers risk attitudes, which follows the expected utility maximization function [5, 22, 25], [41]. The ELCE, allows for the estimation of the certainty equivalence for any risky prospect, by giving what economist referred to as an equally likely weight to the probability of occurrence of either of the prospect. Intuitively, in the application of ELCE model, the individual decision-maker is confronted with two-state risky prospects having an equal probability of 0.5 for each state. Although, the method, overcomes the criticism of bias due to probability preference, it still has some identified difficulty. That is, the decision-maker is forced to choose between a certainty and a lottery. Nevertheless as noted by the proponents of this model, this problem is minimized by presenting the questions as practical decision-making problem [91, 12]. Empirically, under the ELCE model, the individual risk attitudes are appraised according to their choice between hypothetical but realistic prospects alternatives involving a risky situation versus a certain outcomes. In line with the computational flexibility of the ELCE, this study will employ it to elicit the risk attitudes of cassava farmers in the Techiman Municipal Assembly in the Brong Ahafo Region of Ghana.

Theoretical basis for measuring adoption of agricultural technologies

According to literature, empirical study on the diffusion of agricultural innovation became a prominent research field after the publication by Ryan and Gross [82], who analysed farmers' adoption of hybrid corn seed in Iowa [68]. To understand farmers' decision-making process with regard to adoption of new technology, several theoretical models have been developed. Generally, the spread of technology among farmers over time is referred to as the diffusion of the technology. Rogers's classic definition considers diffusion of technology as the process by which the technology is communicated through certain channels over time among members of a social system [81]. By implication, diffusion can be considered as the cumulative pattern of individual adoption decision in time. That is, the timing of individual farmer's decision about adopting, rejecting, or discontinuing the use of a technology [68].

As noted by Rogers, adoption is seen as the decision to make full use of a technology, which encompasses the mental process that an individual farmer undergoes from first hearing about to finally adopting the technology [81]. The empirical evidence from early studies on technology adoption gave a strong foundation to the explosive expansion of adoption research. The several generalizations on the adoption process gave rise to the several classical adoption models, notable among them is Rogers's diffusion model. The conceptual foundation of Rogers's model was that, for adoption to occur, there need to be a mechanism that will facilitate users access to information on the said technology [80, 81]. Rogers's model further stipulates technology adoption by famers is influences by five main characteristics of the technology: Relative advantage, compatibility, trialability, observability, and complexity. Relative advantage of the technology reflects the degree to which a technology is perceived as better than the idea it supersedes. This may be measured in economic terms or social terms. The greater the perceived relative advantage of the technology, the greater it change of being adopted. On the other hand, compatibility reflects the degree to which a technology is perceived as being consistent with the existing values, past experiences, and needs of potential adopters. Thus a technology that is not compatible with the prevalent values and norms of a social systems will not be adopted. Furthermore, Rogers' defined complexity as the degree to which a technology is perceived as difficult to understand and use. Trialability as a factor reflects the degree to which a technology may be experimented with a limited basis. That is, the technology must present less uncertainty to potential users. Finally, observability focuses on the extent to which the technology is visible to others or becomes visible to others. That is the easier it is for individuals to see the results associated with the technology, the more likely they are to adopt. By implication observability stimulates peer discussion of the new technologies among farmers. Another theory that was based on in measuring technology adoption is the Theory of Reasoned Action (TRA), developed by Ajzen and Fishbein in 1975 [7]. The theory is designed to explain human behaviour by highlighting two factors that affects behavioural intention. These factors are attitude towards behaviour and subjective norms. Conceptually, TRA stipulates that a person's attitude towards a particular behaviour is a product of the strength of beliefs and the corresponding evaluations of the consequences.

Intuitively from the theoretical explanations, it been can be summarized that the adoption decision of farmers in the broader sense centres on the concept of individual utility maximization and human behaviour; which could be influenced by factors that cut across, risk and uncertainty, social interactions, technology characteristics, farm and farmer-specific characteristics, among others.

Methodology

Study setting and data

This section describes the study setting and the processes leading to the collection of data used to arrive at its findings. The survey for the study was conducted in the Techieman Municipal Assembly which can be located in the Brong Ahafo Region in Ghana. The Municipality covers a total land area of 669.7 km^2. The area is characterized by a bimodal rainfall pattern. The mean annual rainfall ranges between 1250 and 1650 mm. The average temperature ranges between 30 and 20 °C. The soils in the area are favourable for the cultivation of food crops such as yam, cassava, maize, vegetables, and plantain, among others [3]. The three main vegetation zones found in the Municipality are the guinea savanna woodland, the semi-deciduous zone, and the transitional zone. Techiman is well known for the production of yam, maize, and cassava as well as cash crops like cocoa, cashew, and coffee, among others. The Techiman Municipality is the home of the famous Techiman Market, the largest food crops market in Ghana, and a major commercial centre in the Region. This chosen study area is considered one of the major agricultural production hubs in Ghana and thus plays a significant role in the production of root and tuber commodities, especially cassava production and marketing [66]. Agriculture intensification technologies in the RTIMP programme (RTIMP_Technologies) were promoted among the cassava farmers in this area selected for the study. In the municipality, agriculture is the main source of livelihood for many households accounting for about 57% of the labour force; and of course, the area serves as the largest food crop basket in Ghana. At the time of the survey, available records at the Municipal Department of Agriculture indicated that there were about 3000 active cassava farmers in the survey area and this was used as a sample frame. Substituting the 3000 sample frame of cassava farmers into Yamane's formula [50], gives an estimated sample size of about 375 farmers. Then following the fact that a higher sample size reduces the random error [74] and also to get a good representation of cassava farmers across all the 45 major RTIMP operational areas, a higher number of farmers (450) were randomly selected to be involved in the survey conducted.

Through the application of the cluster sampling technique [74], a mix of purposive and random sampling was done to sample 450 cassava farmers from the sample frame. Here, 45 farming communities were identified as the main operational areas where RTIMP intervention had covered in the Techieman Municipality and thus purposively used as clusters. The identification of the operational farming communities was done with the support of the Department of Agriculture and the RTIMP programme office in the municipality. Following [74], each of the 45 operational communities was treated as a separate cluster. Further, a simple random sampling procedure was followed to select ten (10) farmers from each operational community to take part in the survey; arriving at a sample of 450 cassava farmers. Having done the sampling by involving all the major operational communities where RTIMP intervention had covered in the municipality, the margin of error would be minimal such that the study sample would have a good representation of the target population for the survey. This is based on the fact that an equal number of farmers were randomly sampled from all the 45 operational areas where the introduction of the RTIMP had been covered. Further, the structured interview schedule instrument was employed to collect data from the selected cassava farmers. The structured interview schedule covered questions/items on farm and farmer-specific characteristics, risk attitude, social interaction, and adoption level of agriculture intensification technologies in the RTIMP. The instrument consisted of both open and closed-ended questions. During the administration of the interviews, items in the instrument were explained to the farmers to ensure consistency in the understanding of the farmers. Also, the use of the instrument provided opportunities for further probing by the interviewers. To test the reliability of the instrument, a pilot study was carried out before the main survey. All these helped to obtain reliable responses from the farmers during the survey.

Empirical framework for the analytical measurement and modelling of study variables

Measuring nature of social interaction in study context

The study assessed how the interaction between farmers and other change agents and actors in the farmer's communication network influences farmers' behaviour towards the adoption of RTIMP technologies through risk attitudes formation as an intervening impact pathway. The indicator variables of social interaction focused on the specific interactions between the individual farmers and also, the promoters of the RTIMP technology. The study assumes that social interaction leads to the spread of information and knowledge about RTIMP technologies that shape a farmer's inherent decision-making factor (risk behaviour) and thus cause the technology adoption and utilization either directly or indirectly.

To assess the quality and intensity of social interaction in the farmer's communication network, we used a rating scale, 1-to-10. This was to bring much continuum in the measurement and to allow for high-level analysis. Consequently, farmers were interviewed using questions formulated on a 1-to-10 scale-based format, focusing on four main indicators of their interactions with other social actors (input dealers, extension agents, RTIMP officers, output buyers, media outlets, colleague farmers, transporters, and researchers) regarding RTIMP technological issues. The indicative variables used to measure social interactions in the farmers' communication networks were grouped into four main components: frequency, usefulness, effectiveness, and the degree of trust (see [68]). Accordingly, the indicators chosen, measure the frequency of social interaction, the usefulness of social interaction, the effectiveness of social interaction, and trust in information obtained through interactions. The choice of the measurement scale was to allow for the possibility of estimating an approximate index of social interaction in the farmers' communication network based on the four main components. In addition, using the rating scale was considered much more effective for farmer-self assessment of the quality and intensity of their interactions with other actors regarding RTIMP technological issues [46].

Further, we analysed the information gathered from the social interaction matrix, by using summated and ranked means and subsequently, the Kendell coefficient of concordance (Kendell's W) for robustness check. Kendell's W provides a descriptive measure for which the concordance within an individual scoring structure among assessors can be evaluated. Kendell's W picks on a value in the range of zero to one, where zero means no concordance among assessors on the concept being evaluated, and a value of one means a complete degree of concordance (agreement) between assessors on the concept being evaluated [50]. The mathematical model used for the computation of Kendall's W was as follows:

$$w = \frac{12\left\{\sum K^2 - \left(\sum K\right)^2\right\}\Big/ m}{m\lambda^2(m^2-1)}, \tag{1}$$

where: w = coefficient of concordance, K = sum of ranks for each item being ranked, λ = number of items being ranked, and m = number of cassava farmers.

Estimating risk attitudes of farmers

In recent times, the risk attitudes of farmers are gaining prominence in discussions on behavioural determinants of technology adoption in developing countries (see for example [15, 26]). This research study augments the literature by seeking to investigate the risk behaviour of cassava farmers and how that is influenced by farmers' interactions with others in their social climate to explain the technology adoption decision-making process leading to implementation outcomes of RTIMP cassava technologies.

To understand the risk attitudes of farmers in relation to RTIMP, the current study adopted the Equally Likely Certainty Equivalent (ELCE) estimation approach (see [22, 25]. The ELCE is considered the most common and efficient method used to elicit individual utility functions, which has seen many applications in empirical studies involving farmers in developing countries (see for example [5, 22, 25]) in a similar context. As a modified form of the von Neumann–Morgenstern (N-M) model, the ELCE model helps to avoid bias caused by probability preferences through the use of ethically neutral probabilities {i.e. P = (1-P) = 0.5}. Technically, the ELCE model starts with a simple lottery of 50:50 probabilities. This must include the favourable and unfavourable possible outcomes of the decision problem presented to the decision-maker; which in this study's case, is the cassava farmer. In the application of the model, the decision-maker is asked for a certain prospect (certainty equivalence [CE]) that he/she will accept to make him/her indifferent between a certain sum or a risky prospect. In this, the upper and lower boundaries of the utility function were set at favourable and unfavourable possible outcomes. Based on whether the certain amount is greater than, equal to, or less than the expected value of the risky prospects, each farmer can be classified as risk-loving, risk-neutral or risk-averse. In practice, the expected value is the weighted average of all possible values, the mathematical exposition is explained below.

Assuming that, w, is a random variable distributed as w_j with associated probabilities α_j (where, $\sum \alpha_j = 1.0$), then the expected utility function of the risky prospect to the individual farmer is given by $E[u(w)] = \sum_j \alpha_j u(w_j)$. Accordingly, the expected value of w is given by

$$w^* = \sum_j \alpha_j w_j. \tag{2}$$

The certainty equivalence is then defined as a certain sum of money that gives the same level of utility as the random prospect.[1] Consequently, the certainty equivalence is the amount w_0 such that

[1] For example, if an individual is asked to indicate the certain income that he or she would need to be indifferent between receiving that amount and a lottery with the highest possible win of GH¢10,000.00 and the lowest of GH¢1000.00, each with a probability of 0.5. Here the upper amount of GH¢10,000.00 defines the favourable possible outcome, hence, a utility of that is set at 1 (i.e.$u(10,000) = 1$). The unfavourable possible outcome is GH¢1,000.00, hence, it utility is set at 0 (i.e.$u(1,000) = 0$). The expected value of this possibility is obtained by finding the average of the favourable and unfavourable outcomes, and this gives a value of GH¢ 5500 [*i.e.*, $\{(10,000 + 1000)/2\} = 5500$].

$$u(w_0) = E[u(w)].$$

Operationally, the risk elicitation process in the study experiment involved asking the farmers to choose between alternatives: Alternative I, being a lottery ticket (farming prospect) of either winning a GH¢10,000 or GH¢0 on 50:50 probability and Alternative II, receiving a certain sum of money say GH¢ 3000. If the farmer chose the cash amount over the farming prospect, the same question is posed but the cash amount is lowered (e.g. to GH¢ 2500). On the other hand, if the farmer chose the farming prospect (lottery ticket) over the cash amount, the same question is posed but the cash amount is increased (e.g. to GH¢ 3500). This line of questioning is followed until the farmer becomes indifferent between taking the risky farming prospect and taking the cash amount. Following this, the point at which the farmer becomes indifferent represents the Certainty Equivalence (CE). After, the first CE is obtained the same process is repeated by presenting the farmer with all the lottery tickets containing different options till all the CE values are completely elicited accordingly.

Further, we matched the derived certainty equivalents with their respective utility values and then used the cubic utility function (as presented in Eq. 3) to estimate the utility of individual farmers [20, 94],the cubic utility function (as adopted from [20, 94] are proven to be consistent with risk aversion, risk-seeking, and risk indifference attitudes:

$$U(w) = \alpha_1 + \alpha_2 w + \alpha_3 w^2 + \alpha_4 w^3. \tag{3}$$

We then transformed the shape of the individual utility functions into absolute risk aversion coefficients following Ullah et al. [94] as mathematically defined as below:

$$Ra(w) = -\,{}^{u'}\!/_{u''(w)}. \tag{4}$$

where Ra is coefficient of absolute risk aversion, and u' and u'' are first and second derivatives of income, W. The coefficienct of the absolute risk aversion is positive if individual is risk-averse, negative if individual is risk-seeking, and zero if individual is risk-neutral.

Recursive bivariate probit (RBP): formal modelling of the relationship between social interaction, risk attitude and RTIMP adoption decision

In an economic model fitting for econometric estimation, one major issue that poses a challenge is the problem of endogeneity of the explanatory variables of interest (risk aversion in the study context) which poses limitations to covariate adjustment in estimation and may yield estimates that are not efficient (i.e. bias and inconsistent). Again, other issues that need to be given attention in the model fitting exercise are the possible presence of a nonlinear covariate-response relationship and how this changes when considering the whole response variable distribution [49]. Instrumental variable techniques are mostly used in the economic literature for isolating the effect of a given predictor in the presence of unobserved confounding (see, for instance, [49, 61, 98]. For binary outcome and binary treatment variables, the established instrumental variable estimators are Generalized Method of Moment (GMM), Structural Mean Model (SMM), and Maximum Likelihood (ML) estimators (see, for example, [40, 52, 61, 96]. However, the maximum likelihood estimator, the Recursive Bivariate Probit (RBP), and its semiparametric extension represent an effective way to estimate the effect that a binary regressor has on a binary outcome in the presence of unobservables whiles accounting for any severe consequences on the estimation of covariate effects that can be due to undetected nonlinearity [58]. In the context of our current study, the effect of the binary regressor (i.e. risk aversion or otherwise) on a binary outcome (RTIMP adoption rate—high or low) in the presence of unobservables with the possible presence of nonlinear covariate (i.e. social interaction variables)-response relationships are examined. This thus justifies that following the maximum likelihood (ML) estimation of the Recursive Bivariate Probit addresses our study objectives.

As a natural extension of the probit regression model, in Bivariate Probit modelling, the stochastic terms in the two equations are assumed to be correlated [40]. The recursive version, Recursive Bivariate Probit, [44, 55] which is formally specified as in Eq. 5 below (see also [49, 59], allows for the estimation of the effect of variable of interest (risk aversion) whiles accounting for the problem of endogeneity:

$$\begin{aligned} y_{1i}^* &= x_{1i}^{\tau}\beta_1 + \varepsilon_{1i}, \\ y_{2i}^* &= \alpha y_{1i} + x_{2i}^{\tau}\beta_2 + \varepsilon_{2i}, \\ i &= 1, \ldots, n, \end{aligned} \tag{5}$$

where n denotes the sample size and y_{1i}^* and y_{2i}^* continuous latent variables which determine the observed binary outcomes $y_1(1,0)$ and $y_2(1,0)$ through the rule $y_{vi} = 1_{(y_{1i}^*>0)}$, for $v = 1, 2$. Further, $x_{1i}^{\tau} = (1, x_{12i}, \ldots, x_{1p_1i})$ is the *ith* role vector of of the nxp_1 model matrix X_1 and β_1 is a parameter vector. Similarly, x_{2i}^{τ} is the *ith* role vector of of the nxp_2 model matrix X_2 and β_2 is a parameter vector, whiles α is the parameter vector of the endogenous binary variable y_{1i}. The error terms $(\varepsilon_{1i}, \varepsilon_{2i})$ are assumed to follow the distribution $N([0,0],[1,\rho,\rho,1])$, where ρ is the correlation coefficient and the error variance are normalized to unity. This is because the parameters in the model can only be identified up to a scale coefficient [34, 40, 49, 53, 59].

To identify parameters in the ML estimation technique, it is typically assumed that exclusion restriction on the exogenous covariates holds Marra and Radice [60]; [43, 49, 61]. By implication, the covariates in the y^*_{1i} equation should contain at least one or more regressors (normally called instruments) not included in the y^*_{2i} equation in (5). Here, it is assumed that these regressors have to induce variation in y_{1i} and not have to directly affect y_{2i}; they have to be independent of $(\varepsilon_{1i}, \varepsilon_{2i})$ given covariates [34, 53, 59]. Accordingly, Marra and Radice [60] proposed an estimation of the RBP to account for the presence of this nonlinearity to curtail any consequences in the estimation of covariates effect in situation where it is neglected; and their model fitting has been welcomed in econometrics and widely applied (see for example, [34, 40, 49, 53]. In the generalization of the parametric model versions, continuous covariate effects are modelled flexibly as follows:

$$y^*_{1i} = m^{\tau}_{1i}\theta_1 + \sum\nolimits_{k_1=1}^{K_1} f_1k_1(z_1k_1i) + \varepsilon_{1i},$$

$$y^*_{2i} = \alpha y_{1i} + m^{\tau}_{2i}\theta_2 + \sum\nolimits_{k_2=1}^{K_2} f_2k_2(z_2k_2i) + \varepsilon_{2i}, \quad (6)$$

where y^*_{1i} and y^*_{2i}, and α are same as defined in (5); vector m^{τ}_{1i} is the parametric model components (such as the intercept, dummy and categorical variables) and θ_1 is the corresponding parameter vector; the f_1k_1 are unknown smooth functions of the k_1 continuous covariates z_1k_1i. Further, in the endogeneity case, α is, assumed and thus, allowed to be different from zero; vector m^{τ}_{2i} is the parametric components with coefficient vector θ_2; the f_2k_2 are unknown smooth terms of the k_2 continuous covariates z_2k_2i. The error terms are assumed to follow the distribution $N([0,0],[1,\rho,\rho,1])$, where ρ is the correlation coefficient and the error variance are normalized to unity [34, 53, 59].

Our empirical estimation of (6) was done following the maximum likelihood estimation technique (see [34, 40, 49, 53, 59]). Here, we first contextualized the specification of the model using our empirical variables under study as follows: y_{1i} binary risk aversion (i.e. 1 if a farmer is risk-averse or 0 if otherwise); y_{2i}—binary RTIMP adoption rate (i.e. 1 if high adoption or 0 if otherwise); m^{τ}_{1i}—intercept, sex, age, education, farming experience, household size, access to credit, extension visit, revenue from sales of farm output; z_1k_1i—instrumental variables (social interactions—frequency, usefulness, effectiveness, trust level); m^{τ}_{2i}—intercept, RTIMP technology characteristics, sex, age, education, farming experience, household size, access to credit, extension visit, revenue from sales of farm output. The operational description of these variables that were empirically modelled is presented in Table 1.[2] The choice of the empirical variables that were used to build the model in the context of our study are based on the review of theoretical literature (see [1, 97] and previous empirical studies (see for example [25, 27], Akudugu et al. [9] on risk aversion and agricultural technology adoption.

Average treatment effect: Impact evaluation of the socio-economic programme is usually characterized by difficulty in the random assignment of treatment, since individuals may choose to fully participate or opt-out. This decision behaviour of individuals creates a condition of selectivity bias and endogeneity problem when estimating the potential impact of the treatment variable on the outcome variable. To address this estimation challenge, estimating a regression adjustment average treatment effect model offers efficient and unbiased estimates compared to the standard regression model. The theoretical underpinning of the average treatment effect model is that two potential outcome variables are possible based on the treatment assignment for each population unit: Y (0)—outcome without treatment and Y (1) —outcome with treatment [50]. Given the binary treatment indicator variable W; W (1) denoting the treatment and W (0) denoting the control, the causal effect of the treatment variable on the outcome variable is formally represented as below:

$$Y_i(1) - Y_i(0).$$

From a counterfactual perspective, the estimation of the population average treatment effect (ATE) in the total population based on the treatment indicator and the counterfactual outcomes is formally defined as follows:

$$Y_{\mathrm{ATE}} = E\left[Y_i(1) - Y_i(0)\right].$$

In the study context, the effect of the y_{1i} (i.e. binary risk aversion) is of prime interest in the RBP; but because latent variables do not typically have well-defined units of measurements, the parameter α in the model may not be interpretable [49, 61, 59]. For this reason, we followed the approach by Ieva et al. [49], Marra et al. [59], and Marra and Radice [59] to calculate the effect of y_{1i} (i.e. risk aversion) on the response (RTIMP adoption) probability $p\langle y_{2i} = 1|y_{1i}\rangle$; using the average treatment effect (ATE).

[2] The results and discussions of the socio-economic characteristics of the farmers used as control variables in the model estimation are presented as the Appendix.

Table 1 Summary description of the variables used in the RBP model equations

Variables	Description	Measurement	Apriori expectations	
			AD equation	RA equation
Dependent				
Adoption (AD)	Adoption rate: high adoption rate or low adoption rate	Dummy	NA	NA
Risk attitude (RA)	Whether a farmer is risk- averse or otherwise	Dummy	NA	NA
Independent variables				
Risk attitudes	Whether a farmer is risk- averse or not	Dummy	±	NA
Social interaction				
Frequency	Frequency of interaction among farmers and other actors	Continuous	+	±
Usefulness	Usefulness of the interaction to farmers	Continuous	+	±
Effectiveness	Effectiveness of the interaction	Continuous	+	±
Trust level	Degree of trust on information	Continuous	+	±
Age	Age of farmer	Continuous	±	±
Sex	Sex of farmer	Dummy	±	±
Education	Educational level of farmers	Continuous	+	±
Farming experience	Years of farming experiences	Continuous	+	±
Household size	Household size of farmers	Continuous	±	±
Access to credit	Farmer access to credit facility	Dummy	+	−
Revenue from sales of farm output		Continuous	+	−
Frequency of extension visit		Continuous	+	−

Now, given estimates for the random effects, parametric and smooth functions components, the ATE can be estimated as follows [49]:

$$\frac{1}{n}\sum_{i=1}^{n}\frac{\Phi_2\left(\widehat{\eta}_{2i}^{(y_{1i}=1)},\widehat{\eta}_{1i};\widehat{\rho}\right)}{\Phi(\widehat{\eta}_{1i})}-\frac{\Phi_2\left(\widehat{\eta}_{2i}^{(y_{1i}=0)},-\widehat{\eta}_{1i};-\widehat{\rho}\right)}{1-\Phi\left(\widehat{\eta}_{1i}\right)}, \tag{7}$$

where Φ and Φ_2 are the distribution functions of a standardized univariate normal and a standardized bivariate normal with correlation ρ [49]. Also, the $\widehat{\eta}_{2i}^{(y_{1i}=r)}$ in (7) indicates the linear predictor evaluated at r equal to 1 or 0. The interpretation of the measure is quite straightforward; it tells how the probability of $y_{2i}=1$ (i.e. above-average RTIMP adoption in our study context) changes if $y_{1i}=1$ (i.e. risk-averse farmer in our study context) compared to $y_{1i}=0$ (i.e. non-risk averse farmer in our study context). Further, ρ coefficient which is useful in determining the presence of unobserved confounding (endogeneity) is of great interest to test the model fitting. ρ can be interpreted as the correlation between the unobserved confounders between the equations (Monfardini and Radice 2008 as cited in [49]. Hence, if $\rho=0$ then ε_{1i} and ε_{2i} are uncorrelated and thus there is no problem of endogeneity. By implication, estimating the second equation in either (5) or (6) will yield consistent results.

Summary description of variables in the model

Results and discussion

Social interaction in the cassava farmers' social network

One major challenge to smallholder farmers in developing countries is limited access to timely and adequate information on production technologies and marketing [6, 57, 64]. It is largely believed that social interaction between and among farmers as well as other actors yields many economic returns by directly or indirectly facilitating cooperation and the flow of technical knowledge and information [30, 31]. This by extension implies that the nature of social interaction among farmers to whom the technology is being introduced is one of the key factors for the successful adoption of any agricultural technology. The study, therefore, sought to assess the nature of social interaction among cassava farmers, and the results are presented in Table 2. This covers four key indicators, namely frequency, usefulness, effectiveness, and degree of trust.

Table 2 Assessing the nature of social interactions in cassava Farmers' network

Farmers' interactions in their social network	Frequency		Usefulness		Effectiveness	
	Mean score	Mean rank	Mean score	Mean rank	Mean score	Mean rank
Farmer's interaction with the main promoter of innovations (RTIMP outfit)	6.48	5.55	6.17	5.28	6.13	5.38
Farmer's interaction with other technical change agents (researchers, Agricultural Extension Agents (AEAs), Non-governmental Organization (NGOs))	6.05	5.05	5.94	5.02	5.98	5.08
Farmer's interaction with other market change agents (input sellers, buyers, transporters)	5.71	4.48	5.57	4.48	5.57	4.48
Farmer's interaction with other farmers (neighbours, relatives)	5.75	4.54	5.69	4.51	5.57	4.39
Farmer's participation in organizational meetings	5.66	4.31	5.82	4.64	5.57	4.23
Access to RTIMP related information from the media	5.45	4.11	5.62	4.38	5.43	4.42
Farmer's conversation with other actors on technological issues	5.53	4.20	5.24	3.93	5.79	4.20
Farmer's conversation with other actors on market issues	5.17	3.77	5.13	3.76	5.18	3.82
Degree of trust of information obtain through social interaction			**Mean score**			**Mean rank**
Degree of farmer's confidence in externally provided technical information			6.21			1.51
Degree of farmer's confidence in externally provided market information			6.16			1.49
Test of degree of agreement in farmers' ranking using Kendall's coefficient of concordance						
Social interaction measure						**Kendall's W**
Frequency of social interaction						0.55**
Usefulness of social interaction						0.45**
Effectiveness of social interaction						0.44**
Degree of trust of information obtain through social interaction						0.20**

Significance: "*"@ 0.1 alpha level,"**"@ 0.05 and "***"@ 0.01alpha level, respectively

Frequency of social interaction

Table 2 presents results on the frequency of social interactions in the cassava farmers' communication network. The aim was to evaluate the frequency of information flow and communication between and among farmers as well as other actors along the cassava value chain. The study assumes that the more frequent the interaction, the greater the probability that cassava farmers and other actors along the cassava value chain will learn to interpret each other's attitudes. Additionally, it is assumed that frequent interaction will increase access to a wide range of information sources and platforms.

Among the items used to rate of frequency of social interaction, farmer's interaction with the main promoter of the RTIMP innovation was rated as the most frequent with a mean score of 6.48 followed by interactions with technical change agents (AEAs, researchers, NGOs) with a mean score of 6.05. This implies that the frequency of interaction was much often. It can further be inferred that, the flow of information between the farmers and these information outfits (RTIMP promoters, AEAs, researchers) was to a large extent commendable and that, the technology promoters were doing all that is necessary to have constant interaction with the farmers so that the success of their intervention could be guaranteed; their effort was positively supported by AEAs, researchers and other NGOs who also frequently interact with the cassava farmers. This further suggests that the degree of how frequent farmers have interaction with the RTIMP outfit was about 65%. With this finding, it stands to mean that they have a better opportunity to communicate pressing challenges associated with RTIMP technology as well as learn the technology better. The finding also suggests that frequent interaction with RTIMP promoters will strengthen farmers' access to information and knowledge for use in production decision-making. As shown in the table, the results further revealed that the frequency of farmers' conversations with other actors on market issues was rated as the least frequent with a mean score of 5.17. This means the intensity to which farmers discuss market issues with other actors was about 52% on average. By implication, when it comes to the avenues for discussing market issues with other actors, farmers are to some extent challenging. Kendall's test statistics were used to evaluate the degree of concordance (i.e. agreement) among farmers in their ranking responses and a value of 0.55 was obtained which was significant at a 5% alpha level. This implies that the degree of concordance among farmers was about 55 percent. Now, these findings imply that any policy and intervention that seeks to speed up the spread of any technology among farmers should understand that neglecting the frequency of interaction between the target farmers and the main promoters and other technical change agents like AEAs and researchers may greatly affect it success.

Usefulness of social interaction

The decision to utilize new technical knowledge depends on its usefulness as perceived by its potential users. This often is influenced by social learning through interactions. The study, therefore, sought to analyse the value farmers place on social interaction in terms of its usefulness. From Table 2, results on farmers' inclination toward the usefulness of social interaction show that farmers' interactions with the main promoters of RTIMP as well as other technical change agents were rated as the most useful with the mean score of 6.17 and 5.94, respectively.

The results obtained stand to mean that in general farmers place more value on their interaction with the main promoters of RTIMP and AEAs, researchers as well as other NGOs. In addition, this finding suggests that when it comes to the usefulness of social interaction, farmers are more concerned with information flow between them and the main promoter of technical innovations, in this instance, the promoter of RTIMP technology and AEAs. It can therefore be inferred that to facilitate effective learning and efficient utilization of knowledge gathered through social interaction, the usefulness as perceived by farmers cannot be overlooked. This is because as already noted how farmers perceive the need for interaction and the usefulness of this interaction, is an important consideration in their decision-making process. To confirm whether there is some level of cohesion or agreement among farmers in their assessment of the usefulness of social interaction, the study further employed Kendall's W test to verify the extent of agreement in the assessment given by the farmers. From the analysis, Kendall's W value of 0.45 was obtained and this was significant at the 5 percent alpha level.

Effectiveness of social interaction

The impulse of this was to ascertain the extent to which information and knowledge learnt through the interaction was able to generate practical and timely solutions for farmers. It has been suggested that maximizing the effectiveness of social interaction is a prerequisite for effective social learning in social development (see, [19, 21]. It also provides a solid foundation for a pragmatic and workable solution to major field problems of farmers. This study assumes that the effectiveness of social interaction as perceived by farmers has implications on social processes such as knowledge transfer, information sharing, consensus building, and power relations. As portrayed in Table 2, farmers rated their interaction with the main promoters of RTIMP as the most effective with a mean score of 6.13. The implication of these findings is that, although there is some appreciable degree of social learning through interaction, the impact of the information shared among the actors along the RTIMP technology needs some attention. This is because the perceived effectiveness of information flow and social learning has the potency to undo all the effort put in by the promoters. When farmers perceived that the information gathered did not achieve much as promised, it discourage their enthusiasm and willingness to continue using the technical knowledge passed to them. Additionally, the pattern of social networks suffers as the linkage is often truncated. When this happens to get farmers to participate in any technological intervention is often met with resistance. To ascertain whether or not there is some level of agreement among farmers on this, the Kendall W test was employed. From the results, Kendall's W value of 0.44 was obtained and this was significant at the 5 percent alpha level. The impulse of this is that there was about 44 percent degree of concordance in the assessment given by the farmers. It can therefore be concluded that among the cassava farmers interviewed when it comes to improving the effectiveness of information flow between them, the key promoters of the RTIMP is paramount. This in turn will result in effective social learning and usage of technical knowledge. This further will help address field problems through effective coordination and feedback.

Degree of trust

If farmers are to understand, imitate, and interact effectively among themselves and with other actors, then trust cannot be understated. It is therefore assumed that lack of trust in any social network limits diffusion of technical knowledge as well as the opportunity for technology adoption. The results as portrayed in Table 2, show that farmers' confidence in externally provided technical information was rated highest with a score of 6.21 ahead of their confidence in externally provided market information. This finding suggests that farmers have a higher trust for information coming from technical experts such as extension officers, RTIMP technical officers, and researchers. This, therefore, gives an indication of the need for improving the extension agent–farmer ratio to facilitate the speed of acceptance of new innovations. Furthermore, building trust among farmers and key actors within the immediate socio-economic environment of farmers will help remove perceived threats and uncertainty associated with new technology. It can further be inferred that when a higher degree of trust is built among the social network of farmers, information can be conveyed accurately and timely, whilst the degree of trust may transmit information slowly as well as distort the information. When it comes to market information can be inferred that trusted information has implications for farmers' responses to price signals which is a key to the profitability of any farm business. The study went on to access the degree of agreement among farmers in terms of the importance they attached to the trust items being evaluated. The result obtained from Kendall's coefficient of concordance test revealed that farmers ranked first in their confidence in the externally provided information, with a mean rank of 1.51. This implies that they attached much importance to trust in information gathered on technical information. This accession was further subjected to further analysis and Kendall's W value of 0.20 as depicted in the table of results stands to imply there was some level of agreement among the farmers in their ranking. This was also found to be significant at the 5 percent alpha level. These results, therefore, imply that the evaluation given by the farmers was not just due to chance but that farmers' perception of the average moves in the same direction. This by inferences suggests that building higher trust for technical information is very necessary for effective social learning and technology adoption [39].

It is worthy of note that on all the items presented to the cassava farmers to rate to measure social interactions (in terms of frequency, usefulness, and trust) in their social network, the items on market and marketing issues were generally rated the least. This suggests that when it comes to opportunities to discuss market issues in the farmers' communication network through social interactions, cassava farmers are challenged with receiving sufficient information. By implication, the effectiveness of information flow and social learning on key market issues in the cassava value change as perceived by the farmers was somewhat low. It can further be inferred that the extent to which social interaction effectively influences farmers' behaviour in relation to market decision-making was somewhat moderate. This situation has the potential of affecting the marketing efficiency and market margin of farmers, as the timeliness and adequacy of the information flow on market trends are somewhat low.

Characterization of farmers' attitudes towards risk

Knowledge of farmers' attitudes towards risk is an essential ingredient for understanding their behaviour and how they mitigate the effect of risk in their production business. As posited by Dadzie and Acquah [25], the economic decision-making process of farmers in Ghana is often affected by the numerous risk they face in their farming business. Some of these risks include production risk, economic risk, natural risk, health risk, and so on. This, therefore, means that knowledge of farmers' attitudes towards risk is imperative for curving out pragmatic measures to mitigate the effect of these risks on the socio-economic processes of the farmers. To elicit farmers' attitudes towards risk, the Equally Likely Certainty Equivalent (ELCE) model was estimated and the results are presented in Fig. 1. Here, farmers were presented with two hypothetical alternatives under given objective probabilities (that is one with a guaranteed payoff and one without). Farmers' choice under these conditions defines their risk attitude. Now based on the outcome of the ELCE experiment, farmers were put into three categories: risk-averse, risk-loving/preferring, and risk-neutral as presented in Fig. 1. The result as indicated in Fig. 1, shows that the majority (75.1%) of the farmers had a risk-averse attitude and 21.6% had a risk-loving attitude. Additionally, 3.3% had a risk-neutral attitude. This result is found to be consistent with other studies [25, 38, 100] which reported similar findings that the majority of the farmers they interviewed were risk-averse. In Ghana, for instance, Dadzie and Acquah [25] found out that majority of food crop farmers in the central region of Ghana were risk-averse. Also, Ghartey et al. [38] in a similar study reported that the majority of cassava farmers in the Awutu-Senya District of Ghana were risk-averse.

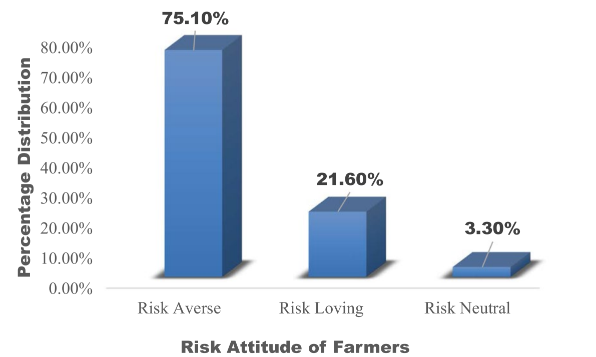

Fig. 1 Classification of farmers based on their attitudes towards risk using ELCE model

Intuitively, the results as depicted in Fig. 1 stand to mean that the majority of the cassava farmers when faced with any business prospect with much uncertainty will go by the safety-first approach irrespective of the promised economic returns. It can further be deduced that on a random basis, three out of four cassava farmers in the study area are risk-averse. This by implication means that the entrepreneurship ability of most of the farmers may be low since they might fear a suffering loss in their

Table 3 Distribution of farmers based on RTIMP technology adoption status

Number of technologies adopted	Frequency	Percent	Adoption status
7	1	0.22	Low adoption rate (below-average adopters)
8	2	0.44	
9	6	1.33	
10	27	6.00	
11	112	24.90	
12	97	21.60	High adoption rate (above-average adopters)
13	63	14.00	
14	38	8.40	
15	58	12.90	
16	42	9.30	
17	4	0.90	
Total	450	100	
Summary statistics			
Mean; standard deviation	12.7; 1.9		
Median	12		
Mode	11		

investment and economic decision-making in their farm business. Additionally, farmers will prefer to have a production technology that gives constant returns to scale than one which promises higher increasing returns with a probability of occurrence [23, 29, 71]. Furthermore, most of the farmers would tend to be sceptical and less willing to adopt any new and improved production technology perceived to be risky, irrespective of the greater economic returns they stand to gain. Consequently, farmers in general will chose a prospect with sure returns although small, than a prospect with uncertain returns although it promises higher gain. In sum, the results from Fig. 1, suggest a higher loss-aversion propensity among cassava farmers in the study area.

Distribution of farmers based on their adoption rate of RTIMP technology

As can be seen from Table 3, the average farmer had at least adopted some components of the RTIMP cassava technology presented to them. With this, it become necessary for us to focus on exploring the extent to which these RTIMP cassava technology package has been adopted by each respondent-farmers which enabled us to compute individual farmers' adoption package counts to arrive at the adoption rate. This was determined by taking the actual counts of the RTIMP technology components adopted by the i^{th} farmers. As could be seen in the table, the total count of technology components expected to be adopted by the i^{th} farmer was 17 which are spread under four broad component areas (i.e. land preparation component, improved planting material or high yielding varieties component, planting technology component, and improved cultural practices component). Using the distribution of the farmers' adoption package counts, we grouped farmers' adoption rate into high adoption rate and low adoption rate (see Table 4). The farmers with a high adoption rate (above-average adopters) were farmers with adoption package counts greater or equal to the mean expected adoption package counts. On the other hand, farmers with a low adoption rate (below-average adopters) were farmers with adoption package counts less than the mean adoption package counts.

The average adoption count was found to be about 12 on a range of 7 to 17 counts of RTIMP technologies adoption among the cassava farmers. Accordingly, we resolved that the average count of technology adoption of 12 becomes a threshold minimum count for the adoption of RTIMP technology in the study area based on which we grouped cassava farmers according to their adoption decisions. As could be observed from Table 3, the adoption rate of 67.1% of our sampled farmers was found to be high (i.e. above-average adopters) and the remaining 32.9% had a low adoption rate (i.e. below-average adopters). Farmers with a high adoption rate are considered to have adopted a reasonably sufficient number of RTIMP technologies necessary to generate higher impact gains on production and income from cassava farming. It is, however, acknowledged that given the threshold minimum adoption technologies of 12 to adjudge farmers' adoption decision into a high adoption rate category, there is still some significant adoption gap (i.e. about 5 more technologies to be adopted even among the above-average technology adopters) with respect to the RTIMP cassava technology among the farmers in the study area. This acknowledgment is informed by the fact that only a few (i.e. 10.2%) of the cassava farmers sampled have adopted almost all the RTIMP technologies introduced to them. It is therefore imperative for stakeholders (especially, technology promoters, and other technical change agents like AEAs, researchers, and NGOs) that matter in cassava value chain improvement to collaborate effectively to address the adoption gap among the cassava farmers.

Empirical nexus revealed: social interaction–risk attitudes–RTIMP adoption decision of cassava farmers

The connections between social interaction, risk attitudes, and technology adoption in recent times have been of much importance to researchers. According to Singh, Gaurav, and Ranganathan, [89], understanding the social context within which risk attitudes are formed and social participation decisions made it necessary for the

Table 4 Semiparametric recursive bivariate PROBIT model results: explore effect of social interaction on risk attitude, and risk attitudes on RTIMP adoption decision

Variable	Variable notation	Parameter estimate	Standard error	*p* value
A. Risk aversion equation				
Constant	θ_{10}	1.617000***	0.493000	0.00
Age	X_1	0.386000 *	0.185000	0.04
Sex	X_2	− 0.013300	0.010500	0.20
Household size	X_3	0.063600	0.039800	0.11
Education	X_4	− 0.014200	0.017000	0.42
Years of farming experience	X_5	− 0.004150	0.026100	0.87
Frequency of access to extension services	X_6	− 0.159000***	0.043900	0.00
Access to microcredit	X_7	− 0.598000**	0.262000	0.02
Revenue from sales of output	X_8	− 0.000119***	0.000027	0.00
Smooth term variables		**Edf**	**Chi-sq**	***P* value**
Frequency of social interaction	S_1	1.00000	1.52000	0.22
Usefulness of social interaction	S_2	2.41000**	7.90000	0.05
Effectiveness of social interaction	S_3	1.00000*	2.85000	0.09
Degree of trust	S_4	5.07000***	17.89400	0.01
B. RTIMP adoption equation				
Constant		− 2.040000***	0.665000	0.00
Risk aversion	Ys_1	1.150000***	0.435000	0.00
Ease of use	Z_1	0.024300	0.064600	0.71
High yielding	Z_2	− 0.093600	0.075400	0.21
Relative advantage	Z_3	0.014900	0.039900	0.71
Compatibility	Z_4	0.135000**	0.066880	0.04
Age	X_1	− 0.285000*	0.153000	0.06
Sex	X_2	0.010400	0.008900	0.24
Household size	X_3	− 0.020420	0.036400	0.51
Education	X_4	0.027600*	0.015100	0.07
Years of farming experience	X_5	0.035500	0.024500	0.15
Frequency of access to extension services	X_6	0.047500	0.044500	0.29
Access to microcredit	X_7	0.584000***	0.211000	0.00
Revenue from sales of output	X_8	0.000075***	0.000022	0.00
	Model summary			
	n	450		
	LogLik	− 395.69		
	Rho (ρ)	0.20		
	ATE of risk aversion	− 0.38 (37.9%)	CI (− 0.55 − 0.09)	

Significance: "*"@ 0.1 alpha level,"**"@ 0.05 and "***"@ 0.01alpha level, respectively

promotion of agricultural technology. This study, therefore, assumes that in order to improve the adoption rate of RTIMP technologies among cassava farmers, it is necessary to understand the social context within which risk attitudes are formed and social participation decisions are made. Following the theoretical proposition by Singh et al. [89], the study empirically investigated the null of "nature of social interactions among farmers significantly influences farmers' attitudes towards risk which consequently influence significantly, the adoption decisions of farmers". The study achieved this objective by estimation of recursive bivariate probit endogenous regression model and the results are presented in Table 4. The table of results shows estimates provided by the bivariate probit model for the RTIMP technology adoption outcome (i.e. B in Table 4) and the indicator of risk aversion (i.e. A in Table 4). It can be noticed from the table of results that most of the selected covariates in the model are significant (for example 5 out of 8 socioeconomic variables, and 3 out of 4 social interaction variables, as well as technology compatibility attribute). Again, it is worth noting that the effect of the social interactions is nonlinear, being the smoother degrees of freedom significantly greater than one in the cases of the usefulness of social interaction, the effectiveness of social interactions, and degree of trust as the results in the in Table 4 suggest. Also, our estimation of the correlation of the recursive bivariate probit model resulted in the estimated to be 0.205 and it is significantly different from zero at the 0.05 alpha level. This supports the presence of unobserved confounders and hence the endogeneity of risk aversion effect on adoption decisions which the employed analytical technique accounts for appropriately. In fact, it is usual that some unexplained variability exists in complex social settings where patterns of change could be influenced by the interactive effects of diverse phenomena in multiple relations.

Effect of social interaction on the risk attitudes of farmers

The identification and categorization of farmers' risk attitudes continue to be of utmost importance to both researchers and policymakers. In agreement with Dadzie and Acquah [25], knowledge of the risk attitude of farmers and the factors that influence their attitudes to risk provides an understanding of their behaviour and the measures they adopt to mitigate the effects of the numerous risk they constantly face in their production environment. The results as portrayed in Table 4 show that the effects of the usefulness of social interaction, the effectiveness of social interaction, and degree of trust on risk aversion were significant at, 0.05, 0.1, and 0.01alpha levels, respectively. This implies that these indicators are important predictors of farmer-risk attitudes. Thus to influence farmers' decision-making process, policy frameworks targeting these factors, all other things being equal, will give positive results.

The significant negative effect of the effectiveness of social interaction suggests that farmers who had less effective interactions were more risk-averse in nature. This implies that the lower the frequency of interaction, the more likely a farmer will be risk-averse, hence less willing to take a risk. This result suggests that these farmers choose to go by the safety-first approach to the decision-making paradigm, hence he/she would prefer a prospect with low returns with certainty to a prospect with high expected returns but with uncertainty. Also, this stands to mean that increasing the frequency of social interaction helps removes some of the perceived uncertainties in the socio-economic environment of the farmers. Frequent interaction among farmers and other stakeholders helps to circulate timely and accurate information on the business environment of the farmers and this contributes to their risk management strategies. For instance, timely and accurate information on market prices of inputs and output, help farmers to make effective and efficient decision-making that intends to mitigate risk. This result is found to be consistent with the findings by Singh et al. [89] who reported a negative relationship between social interaction and risk attitude of farmers in Gujarat in India when they investigated the relationship between social interaction and risk attitude and adoption of microinsurance.

Also, the significant effect of the usefulness of social interaction suggests that farmers who perceive their interaction to be less useful have a higher probability of becoming more risk-averse. This means that this group of farmers is somewhat conservative in nature, and has less inclination to make risky business decisions. By inference, when presented with alternative prospects, they would avoid the one for which the probability of failure is much higher. In other words, they would prefer a prospect with a certain outcome even though it promises a lower return over a prospect with a higher potential return but with some degree of uncertainty.

It can further be noted that the degree of trust was inversely related to risk attitude. This implies that the farmers who perceived the degree of trust to be low were more risk-averse in attitude. Inversely, the results also suggest that the higher the degree of trust, the more likely a farmer is willing to take a risk. Additionally, these results suggest that the level of optimism among the farmers in the social network pattern is to a large extent influences their risk decision-making behaviour in being more sceptical about investment options. For instance, when facing a contract decision that presents say price risk and the contract partner's level of opportunism, a farmer with higher risk aversion will not trust the transaction, hence more likely to opt-out. This means that there is an indirect relationship between the degree of trust that exists among members of the social system and the intensity of technology adoption. As suggested by Akinwunmi, Olajubu, and Aderounmu [8], users of any technology need to be assured of its safety and reliability of the technology while using it. One way to do this is to build confidence around the technology and reduce the level of uncertainties and this requires trust. Thus, building a higher degree of trust among farmers will increase the intensity of the adoption of the RTIMP technologies in the long run. Trust as a social variable is perceived to either increase or decrease the risk and uncertainties potential adopters of any technology may have about that technology. Hence it is imperative to always consider measures on how to build strong trust among members of any social system when it comes to the introduction of new innovations. This result agrees with that of Belanche et a l. [18] who opined that trust has a positive effect on the technology acceptance among members of social systems when they analysed the role of trust in the technology acceptance model. This means that when trust is high in their social network, farmers' confidence in technology acceptance is built, and thus would not hesitate to positively adopt new technologies. The above results confirm the findings by Hailu et al. [42] who reported that the intensity of social interaction has significant positive effects on the adoption decision-making process of dairy producers in Ontario.

Effect of risk attitudes on RTIMP adoption decision of farmers in the midst of technology characteristics

The result reveals that the risk attitude of farmers had a negative effect on RTIMP adoption and this was significant at the 0.01 alpha level. This suggests that farmers with a risk-loving attitude had a higher intensity of adoption. Further, the results in Table 4 show the average treatment effect (ATE) estimate of risk aversion on RTIMP adoption to be 0.379 which is negative. This is consistent with the reasoning that the lesser the degree of risk aversion among cassava farmers, the more likely that they would adopt RTIMP technologies introduced to them. The point estimated ATE implies that in the presence of confounders (either observed or unobserved), decreasing the degree of risk aversion would have about 38% probability of explaining the likelihood of adoption of RTIMP technologies by the cassava farmers. With this, our concerns about the detrimental effects of unobserved confounders on the effect of interest (risk attitudes of farmers) are accounted for; and thus the use of the recursive bivariate probit model was appropriate to allow for more reliable inferences.

Accordingly, farmers with a risk-loving attitude had adopted the RTIMP technologies more than risk-averse farmers. By inference, the more a farmer is risk-loving the higher the likelihood of him/her increasing the intensity of adoption. Following the theories on the decision-making process farmers often chooses between risky and uncertain prospects by comparing expected outcomes to maximize their profit or socio-economic benefits. Thus farmers with high risk aversion when they perceived much uncertainty around an innovation, feel less willing to take the risk of adopting it. These farmers often adopt the safety-first principle in their decision to whether adopt and if they do often tread cautiously. However, farmers with a high preference for risk are very optimistic and thus are much more open to trying new technology that promises a high return on investment, by placing a higher preference on the lower probability of making of gain than the high probability of making a failure. The above results suggest that risk-seeking cassava farmers in the study are more inclined to take risky action in terms of their adoption of the RTIMP technology. This empirical finding confirms the report by Yu [102] who reported that diary farmers in Ontario who had a risk-loving attitude were more willing to adopt the new genotyping technology. It is acknowledged that technology adoption is a choice that is made after a period. Usually, it is not a consequence of the economic results of just one year. However, the analysis in the current paper was carried out on a cross-section and considered risk aversion over one year. Changes in risk attitudes over a period due to external (and in most cases unpredictable) shocks can strongly influence the farm's choices. Therefore, this limitation of the study data is noted; consequently, the survey's outcome is made cautiously bearing in mind the limitation to establishing a strong lasting relationship between risk and technology adoption without considering the dynamism of the phenomenon and the multi-year process used to decide to invest in agricultural technology by farmers. Future research in relation to this study must take this into account.

The results further revealed that compatibility of technology with the current practice of farmers had a positive effect on the higher probability of adoption of RTIMP technology by cassava farmers and this was significant at a 0.05 alpha level. This implies that the higher the compatibility of technology, the higher the probability of adoption of RTIMP technologies by farmers. The result confirms the assertion that the adoption of innovations is significantly dependent on the relative attributes of the technology (see for instance [86, 95]).

Socio-economic characteristics on risk attitudes and adoption

On the effect of socio-economic variables, the estimated model results show that age, education, extension contacts, access to credit, and farm income all have significant effects on risk aversion and RTIMP technology adoption among cassava farmers. Age has a positive significant effect on risk aversion but a negative significant effect on RTIMP adoption decisions of cassava farmers and these are consistent with apriori expectations. The positive relationship between age and risk aversion implies that the more aging a farmer is the high the probability of becoming more risk-averse. With youthful exuberance, younger farmers would not hesitate to take the risk especially when it comes to an inclination to try new things introduced to them compare to older farmers. The negative beta coefficient for age suggests that the intensity of adoption increases among farmers in lower age brackets. This, therefore, suggests that younger farmers tend to adopt the RTIMP technology at a higher intensity than older farmers. The sign of the beta coefficient of age further implies that a unit increase in the age of farmers results in a 0.1055 point decrease in the intensity of adoption. The above finding on age confirms the finding by Owusu and Donkor, [73] who reported that there is a negative relationship between age and the extent of adoption of improved cassava varieties in the Sekyere South district in the Ashanti region of Ghana.

The results portray that education has a beta coefficient that is significant at the 0.1 alpha level. The education effect is positive on RTIMP technology adoption. This implies that the more educated a farmer is the higher the probability of adopting the technologies introduced to them. The findings confirm the argument put forward by Filippin and Crosetto [33] that the general conclusion in the literature that educated farmers often easily understand technology concepts and that facilitates their willingness to adopt is often the truth. From the table, it can also be seen that the beta coefficient of frequency of extension visit received was significant at 0.01 alpha level. The frequency of extension visits was also found to be inversely related to risk attitude. This stands to mean that, farmers who received fewer extension visits are likely to be more risk-averse. In other words, the more extension visit a farmer receives, the less likely he/she will be risk-averse. In general extension, provision is expected to disseminate proven and trusted technological knowledge to farmers. When proper and adequate education is thus given to farmers, it gives them some level of traditional insurance to mitigate against the various risk they face. Furthermore, timely and adequate information dissemination help farmers make informed, effective and efficient production and marketing decision which lowers the expected risk associated with the decision-making process. Additionally, from the findings, it can further be suggested that frequent extension visits help clear some of the doubts and misconceptions that often make them less willing in trying out new innovations.

The results also showed that revenue from sales of farm output had a negative beta coefficient in the risk aversion equation but shows positive significance in the RTIMP_Technologies adoption equation. It shows significance at the 0.01 alpha level. This suggests that farmers who realized low revenue were more risk-averse. In other words, this implies that the lower the revenue obtained from the sales of farm output, the more risk-averse a farmer would be. It can therefore be inferred that higher revenue boosts farmers' confidence and willingness to take on activities and investments that have higher expected outcomes, even though it may carry with them risks of failure. The negative coefficient of access to microcredit on risk aversion suggests that farmers who did not have access to finance have high tendencies to be more risk-averse. Further access to credit shows a positive significant effect on the high rate of adoption of RTIMP technology among farmers.

This could probably mean that with access to credit to finance farm production activities, most of the cost implications that could limit adoption would be eliminated. The general problem of cash traps was therefore might not be an issue, hence enabling farmers to adopt the technology. Based on these results it can therefore be inferred that the programme was able to achieve its goal of attracting the most deprived rural households into cassava production as a means of increasing their food security and income status. This empirical finding is consistent with that of Simtowe et al. [88] who find out that access to credit increases adoption among credit-constrained maize farmers in Malawi.

In general, the results from the recursive bivariate probit model estimates as presented in Table 4 portray that when it comes to cassava farmers' adoption decision-making on the RTIMP technology, the most important driving factors that affect farmers' adoption intensity are risk attitude, perceived usefulness and effectiveness of social interactions, and degree of trust, in the midst of socio-economic (i.e. age and education of farmers, extension contacts, access to credit and increased farm revenue). Furthermore, the above findings confirm that Risk attitudes and social interactions have important implication for the competitiveness of rural farmers as the adoption of new technologies often have the potential to considerably enhance agricultural productivity and farm income. Our empirical findings, therefore, confirm the study hypothesis that social interactions in the social network of cassava farmers significantly contribute to shaping the risk attitudes of the farmers which subsequently influence significantly, their RTIMP technologies adoption decisions.

Conclusion and implications

Over the years the food security and income status of rural households in Ghana have been major concerns to successive governments. To enhance the income and food security status so as to improve the livelihood of the rural poor, the Government of Ghana in collaboration with the intentional Fund for Agricultural Development, initiated the RTIMP programme. As a staple and food security crop in Ghana, cassava value chain improvement was targeted under the RTIMP initiative. In order to improve farm output, income, and standard of living of root and tuber crop farmers, the programme introduced improved cassava technologies to cassava farmers. The current study aimed at examining the adoption impact of RTIMP technologies by exploring the connection between social interactions and risk attitudes of farmers and the implication of the adoption of the technologies. Farmers consider as important, their interactions with main promoters of RTIMP technologies as well as technical change agents including AEAs, researchers, and NGOs, and interactions with other farmers. This they expressed in the frequency, effectiveness, and usefulness of social interactions they had with the listed actors in their information and communication networks as well as a high degree of trust and confidence in the technical information obtained. It was, however, found that farmers are generally challenged with opportunities to receive sufficient information from the information and communication networks regarding the market and marketing of their produce. The study also revealed a higher degree of risk aversion among most the cassava farmers, but it was found that the effectiveness and usefulness of farmers' interactions in their communication networks coupled with a higher degree of trust farmers gain in the information delivered to them through their social interactions with main promoters of technologies, AEAs, researchers, and colleague farmers have significant tendencies in shaping risk attitudes by lowering the degree of risk aversion among farmers. Findings further suggest that the less risk-averse farmers are, the more likelihood of those farmers adopting the RTIMP technologies introduced to them.

The implication of the conclusions above is that to ensure the high adoption impact of innovative technologies among farmers, there is the need to work towards reshaping the risk attitudes by lowering the degree of risk aversion among the farmers which can be achieved significantly through effective dissemination of the technologies such that their usefulness will not be in doubt by farmers; thereby building trust and confidence. It can further be concluded from the predicting factors of adoption that compatibility of technology with current practices of farmers as well as access to credit and extension services positively impact farmers' technology adoption decisions. The following recommendations are made based on the conclusions drawn from the findings: stakeholders in the RTIMP technologies should factor into their action plan the need to build trust among farmers as well as facilitate frequent interaction without downplaying the usefulness and effectiveness of information sharing among farmers. Also, promoters of the RTIMP technologies should consider collaborating with the financial institutions to institute an insurance package as a component of the technology to cushion farmers against risk. The Ministry of Food and Agriculture as the government policy arm for agriculture should take recognizance of the interplay between social interaction and farmers' perception or attitude towards risk in the promotion of any government project. Again, policies by the Ministry of Food and Agriculture that seek to promote the adoption of new innovation should be complemented by desirable instruments that hedge against risk as well as enhance strong social interaction (usefull and effective) among members of the agricultural community.

Appendix

Descriptive characteristics of the sampled cassava farmers

See Tables 5 and 6

Table 5 Description of demographic variables of respondents used as explanatory variables

Variables	Mean	Std. Dev	Minimum	Maximum
Age (years)	43.9	9.9	20.0	74.0
Household size	6.0	3.0	1.0	16.0
Years of farming experience	7.9	2.3	1.0	20.0
Years of formal education	8.1	4.4	0.0	16.0
Frequency of access to extension service	5.0	2.2	0.0	20.0
Revenue from sale of farm output (GH¢)	6202	4732	180	33,000
Sex	Categories		Frequencies	Percentages
	Male		144	32.0
	Female		306	68.0
Membership to association	Yes		390	86.7
	No		60	13.3
Credit access	Yes		395	87.8
	No		55	12.2

Table 6 Description of farmers' characteristics based on their risk attitudes and adoption status

	Adoption status						Attitudes towards risk					
	Below average adopters ($n = 124$)		Above average adopters ($n = 251$)		Test of equality of means		Risk-averse farmers		Non-risk averse farmers		Test of equality of means	
Continuous variables	**Mean**	**Std. Dev**	**Mean**	**Std. Dev**	***t* value**	***p* value**	**Mean**	**Std. Dev**	**Mean**	**Std. Dev**	***t* value**	***p* value**
Age (years)	44.8	10.3	43.7	9.1	1.0	0.30	43.6	9.2	45.1	12.6	0.5	0.60
Household size	5.8	2.5	5.97	2.8	0.6	0.58	5.8	2.5	6.5	1.7	0.8	0.41
Years of experience	7.98	3.3	7.8	3.5	0.41	0.68	7.9	3.2	10.6	4.2	1.9	0.05
Years of formal education	8.4	4.4	7.9	4.5	1.0	0.29	8.2	4.5	7.2	4.1	1.3	0.19
Frequency of access to extension service	4.5	2.0	5.2	2.5	2.6	0.01	5.1	2.4	4.8	2.3	4.1	0.00
Revenue from sale of farm output (GHS)	5159	3574	6719	5139	3.4	0.00	9888.13	5965.41	6110.91	4683.29	2.2	0.03
Categorical variables	**Freq.**	**Percent**	**Freq.**	**Percent**	**Chi-square**	**Asymp. sign**	**Freq.**	**Percent**	**Freq.**	**Percent**	**Chi-square**	**Asymp. sign**
Sex Male	42	28.4	102	33.8	1.2	0.27	214	63.3	45	40.2	1.3	0.25
Female	106	71.6	200	66.2			124	36.7	67	59.8		
Membership Yes	134	90.5	255	84.4	2.4	0.12	299	88.5	89	79.5	5.1	0.02
to association No	14	9.5	47	15.6			39	11.5	23	20.5		
Credit access Yes	131	88.5	264	87.4	0.2	0.69	300	88.8	94	83.9	4.6	0.03
No	17	11.5	38	12.6			33	11.2	18	16.1		

Based on the literature on the determinants of technology adoption (see for example [9, 27], the study investigated some selected socio-economic variables and used them as control variables when estimating the specified econometric model. The descriptive results of these selected farmer and farm characteristics are presented in Table 5. The results on the age of the farmers in the table depict 43.9 years as the mean age of the farmers sampled within the age range of 20 years to 74 years. It can be inferred from the age results that an average farmer in the study area is within the active labour force and thus still have the potential to actively manage their farms' activities. The results in Table 5 also show that only about one-third (i.e. 32%) of the sampled cassava farmers were males with the majority (68%) being females. This is not surprising since women's involvement in the agricultural value chain activities has predominantly been in the area of food crop production where cassava production is significant in Ghana [10, 35]. It is worthy of note that most of the 41.2% of women's involvement in agriculture is mainly in the production of food crops in Ghana. The results in the table further portray that the years of formal education of cassava farmers involved in the survey ranged from 0 to 16 years with an average of 8 years of formal education. It can be noted that the majority (about 86%) of the farmers have had formal education. This suggests that for the majority of the farmers, there is some capacity for them to understand and appreciate components of the RTIMP technologies package transferred to them which would facilitate the adoption of the technologies.

It also is noted from the results that there is a wide variation in the number of people in the households of the cassava farmers. With an average of 6, the household size of the farmers ranges from 1 to 16. By implication, the average family labour capacity for a typical farm family in the survey area stands at 6 and provides a significant production potential since family labour is the main source of farm labour supply, especially in food production activities in rural Ghana. Further, as the results show from Table 5, the average years of farming experience by a cassava farmer involved in the survey are 7.9 years with some having more years of experience up to 20 years. The study results are closer to other studies [54], Audugu et al. 2012; [50], [4] findings in Ghana. This implies that an average farmer in the survey area has sufficient farming experience based on which rational production decisions can be taken to ensure a good production outcome.

Further from the table, it could be seen that the majority (86.7%) of the cassava farmers belong to a farmer-based organization and this is very essential for technology adoption. With the given situation, the promotion and facilitation of technology transfer among farmers would be better enhanced. Furthermore, the results revealed that on average, cassava farmers were able to realize gross revenue of GH¢ 6202 from the sale of their cassava produce within the production period under review. This, therefore, stands to reason that all other things being equal, farmers have the average potential of being able to generate income to significantly contribute to household livelihood improvement. In every business, access to credit is very important to the liquidity status of the enterprise. Hence, the study sought to find out whether cassava farmers have access to credit to finance their farm business, and the results showed that more than half of the farmers (87.7%) do have access to credit. Credit farmers have access was mostly from financial institutions, NGOs, and in some cases, families, and friends. This, therefore, means that majority of the farmers have the ability to readily meet their operating expenses for better productivity growth since credit is mostly used to take care of variable input expenses including fertilizer and labour costs. From the table, it could be seen that the majority (86.7%) of the cassava farmers belong to a farmer-based organization and this is very essential to technology adoption. With the given situation, the promotion and facilitation of technology transfer among farmers would be better enhanced.

The paper proceeds to describe the cassava farmers' socioeconomic characteristics based on their RTIMP adoption status and risk attitudes; the results are presented in Table 6. The purpose here is to examine if there were wide variations in the socio-economic characteristics of the farmers having categorized them based on their adoption status and risk attitudes. The results in Table 6 show that the mean age of below-average adopters of RTIMP technologies is 44.8 years compared to a slightly lower mean age of above 43.7 years computed from the data of above-average adopters. The average years of experience as a farmer is about 8 years for both categories of farmers. The seeming homogenous characteristics of farmers can further be confirmed in terms of the results for education as well as the frequency of access to extension services in Table 6. With farm incomes, the above-average adopters recorded a relatively higher mean income of GHS6719 compared with the GHS5159 for below-average adopters. The results further show that there are more females (i.e. over 65%) than males in both adoption categories of the cassava farmers. The results again portray that a higher percentage of farmers in both adoption categories have had access to credit as financial resources to support their farm business activities. It can be deduced from our results that the cassava farmers in the study area are, largely, homogenous in socio-economic characteristics with respect to their groupings according to their adoption decision categories.

The results for the distribution of the cassava farmers based on their risk attitudes as presented in Table 6 portray that the mean age of risk-averse farmers is relatively smaller than that of the non-risk averse farmers (i.e. 43.6 years compared with 45.1 years, respectively). This means that an average risk-averse farmer is younger than his non-risk averse counterparts in the study area. With respect to household size and years of experience, the non-risk averse farmers have a larger mean size and years of experience. Further, the results of the years of formal education and the number of extension visits in Table 6 suggest that the average risk-averse farmer is relatively more educated and has had more access to extension services compared with their non-risk averse counterparts. The results again show that the mean income of GHS9888.13 is also relatively higher than that of the non-risk averse farmers which was computed to be GHS6110.91. In terms of sex distributions, it can be noted from the table of results that the majority (about 63%) of the risk-averse farmers are males whereas, in the case of non-risk averse farmers, the majority (about 60%) are rather females. Also, the majority of both risk-averse and non-risk averse farmers have membership in farmer-based organizations (i.e. about 89% and 80%, respectively) and have had access to credit facilities to support the financing of their farm work (i.e. about 89% and 84%, respectively).

Abbreviations

RTIMP: Root and tuber improvement and marketing programme; IFAD: International fund for agricultural development; MoFA: Ministry of food and agriculture; EBPs: Evidence based practices; ELCE: Equally likely certainty equivalent; N-M: Neumann–Morgenstern; CE: Certainty equivalence; RBP: Recursive bivariate probit; GMM: Generalized method of moment; SMM: Structural Mean Model; ML: Maximum likelihood; ATE: Average treatment effect; AD: Adoption; RA: Risk attitude; AEAs: Agricultural extension agents; NGOs: Non-governmental Organizations.

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Author contributions

SKND designed the research protocol, wrote the formal and empirical model framework, interpreted and discussed the results and was a major contributor in writing the manuscript; JN did literature search, contributed to the design of the instrument and conduct of survey; EWI analysed and interpreted the data used for the paper and was a major contributor in writing the manuscript, and SA contributed to the design of the instrument and provided technical advice in developing the research protocol. All authors read and approved the final manuscript.

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The datasets used and/or analysed for the current study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate

The research including the instrument sent out for data collection from the cassava farmers was given ethical clearance by the institutional review board of the University of Cape Coast before field survey was conducted. Further, farmers consent to participate in the survey was sought prior to interviews conducted by explaining the purpose of the research and later sought for their voluntary participation.

Consent for publication

All authors have read the final manuscript and given their consent for the submission for publication.

Competing interests

None of the authors have any competing interest in publishing the research paper.

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