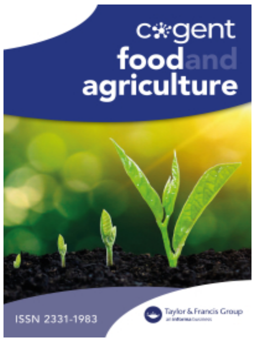

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SOIL & CROP SCIENCES | RESEARCH ARTICLE

Entrepreneurial and attitudinal determinants for adoption of Climate-smart Agriculture technologies in Uganda

Diana Kirungi[1,2]*, Brian Senyange[1], Joshua Wesana[1,3], Haroon Sseguya[2], Xavier Gellynck[1] and Hans De Steur[1]

Abstract: Climate-Smart Agriculture (CSA) technologies have great potential to minimize climate risks, sequester carbon, improve food security, and achievement of Sustainable Intensification (SI) goals. This makes their adoption a necessity for achieving sustainable agricultural systems. Despite the benefits and all efforts, smallholder farmers in developing countries still have low adoption of CSA technologies. This study explored the determinants of intentions to start and continue adopting CSA technologies. A cross-sectional survey based on the Theories of Planned Behaviour (TPB), Diffusion Of Innovations (DOI), and Entrepreneurial Orientation (EO) was administered to 230 randomly selected smallholder coffee farmers in the Luweero district, Uganda. A Multi-group Structural Equation Model (Multi-group SEM) analysis reveals that more factors determine the intention to start adopting CSA than for intention to continue implementing CSA and the same factors could influence the former and the latter differently. Key recommendations to enhance the uptake and continued adoption of CSA technologies include focusing on raising awareness about the characteristics of CSA technologies, employing a multi-stakeholder approach to remove obstacles that hinder CSA adoption and providing business and entrepreneurial skills training for farmers. Our study findings and recommendations will help different stakeholders in designing more suitable and sustainable CSA technology adoption interventions.

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Subjects: Agriculture & Environmental Sciences; Environmental Management; Biodiversity & Conservation; Technology

Keywords: climate-smart agriculture; diffusion of innovations; entrepreneurial orientation; structural equation modeling; sustainable intensification; theory of planned behaviour; Uganda

1. Introduction

Climate change is increasingly affecting agriculture. In the tropics, extreme temperatures and inadequate rains threaten the growth of the agricultural sector (Aydinalp & Cresser, 2008; Tripathi et al., 2016). Climate change is also associated with an increased prevalence of crop pests and diseases, and a decline in soil fertility, leading to crop failure and low productivity (Oseni & Masarirambi, 2011). Predictions show a likely crop yield reduction of 4.5% to 9% due to medium-term (2010–2039) climate impacts and a 25% or more decline due to long-term (2070–2099) impacts (Venkateswarlu, 2017). With almost one-third of the population still below the poverty line, reducing vulnerability to climate change impacts in the agriculture sector is essential to increase incomes and minimize poverty (Branca et al., 2021). This calls for careful management of resources like soil, water, and biodiversity (Mahato, 2014). Climate-Smart Agriculture (CSA) technologies are promoted as adaptation and mitigation strategies for the negative impacts of climate change (Taylor, 2018) and as a foundation and enabler for achieving Sustainable Intensification (SI) goals (Bellamy, 2013; Campbell et al., 2014; Sebatta et al., 2019). CSA is a farming approach that can increase farmers resilience to climate change, improve their livelihoods, and food security (Lipper et al., 2014; Palombi & Sessa, 2013). CSA can also increase carbon sequestration (Rahn et al., 2014), hence contributing to increased efficiency, competitiveness, and sustainability of agricultural systems (Anwar, 2019; Fleischer et al., 2011). Multiple CSA technologies have been identified and developed in varying conditions and contexts (Lipper et al., 2014). These include water conservation, soil fertility management, agroforestry systems, conservation agriculture, physical garden infrastructure, and improved crop varieties (Ampaire et al., 2017; Brown et al., 2018; Kangogo et al., 2021). Their impact has been proven for various crops and in different contexts, as illustrated by increased crop yields of, for example, wheat in China (Sun et al., 2018), coffee in Kenya (Lamanna et al., 2020), and cotton and grain in Pakistan (Sardar et al., 2021). Other studies showed benefits relating to resilience to climate change impacts for Arabica coffee in Ethiopia (Asegid, 2020) and lowering GHG emissions in Indonesian rice fields (Ariani et al., 2018) and in wheat-rice fields in China (Kakraliya et al., 2021). Despite these benefits to meet sustainability goals, previous research indicates slow and largely limited sustained adoption of CSA technologies by smallholder farmers (Nakabugo et al., 2019), yet this is an important prerequisite for the successful implementation of CSA and the sustainability of agricultural systems. This highlights a need for more research on what determines CSA adoption.

CSA adoption studies in developing countries largely focus on food crops including maize (Aleminew et al., 2020; Anwar, 2019), beans, potatoes (Ogola et al., 2021), sorghum (Atsiaya et al., 2023), millet (Anwar, 2019; Vincent & Balasubramani, 2021), cassava (Victory et al., 2022), rice (Anwar, 2019; Ariani et al., 2018), and wheat (Kakraliya et al., 2021; Sardar et al., 2021), and less on export cash crops like coffee (Diro et al., 2022a; Djufry et al., 2022), cotton (Lamanna et al., 2020), cocoa (Abegunde et al., 2019; Dalaa et al., 2020), and rubber (Chandra et al., 2017). Such cash crops provide the farmer with income for most part of the year (Kuma et al., 2019). Farmers can use this income to invest in and improve the management of their farms and stimulate agricultural innovation which in turn increases farm yields also for food crops contributing to food security (Achterbosch et al., 2014). Therefore, proper management of cash crops like coffee is a fundamental strategy towards improving food security in communities where these crops are a major source of livelihoods (Achterbosch et al., 2014; Kuma et al., 2019). Also, some of these cash crops including coffee, cocoa and rubber are plantation crops grown as agroforestry systems that can also play a role in climate change mitigation through carbon sequestration (Chemeda et al., 2022), climate change adaptation (Shekmohammed et al., 2022) and contributing to national development. Coffee, for instance, is a key export earner in Uganda, with annual export revenues of US$17 billion (FAOSTAT, 2018) and contributes 1.5% of the country's Gross Domestic

Product (GDP) (UBOS, 2019). This study will take a critical focus on CSA adoption and continuation in coffee production. In Uganda, coffee plays a very significant role in poverty reduction (UBOS, 2018a the livelihoods of over 12 million Ugandans (UBOS, 2018a). Over the years, the country has experienced slower and fluctuating growth in coffee volumes amidst increased cultivated land (Mulinde et al., 2021). This is attributed to poor agricultural land management practices, limited input use, and environmental degradation that exacerbate climate change impacts (UBOS: 2018a). Hotter and more prolonged dry spells as well as short and extreme rains increase coffee's susceptibility to pests and diseases (Mulinde et al., 2021). It is evident that CSA is necessary to reverse Uganda's declining coffee production trend (Bunn et al., 2019). Despite CSA being highly promoted by several private and public sector stakeholders and also incorporated into several national policy documents (Karlsson et al., 2017; Oliveira et al., 2021), adoption among smallholder farmers in Uganda is still low and of varying degrees with many of the technologies remaining unused (Ampaire et al., 2017; Nakabugo et al., 2019), limiting CSA's full potential (Brown et al., 2018; Makate et al., 2019). The situation is also similar in other developing countries including Kenya, Tanzania, and Malawi where the CSA technology adoption for maize is below 10% (Tesfaye et al., 2017). These variations in adoption rates suggest that there are unique and varying constraints to the uptake of these different technologies (Kurgat et al., 2020) that need further inquiry. However, literature on what determines CSA technology adoption and particularly continued use is sparse and inconsistent (Amsalu & De Graaff, 2007; Nakabugo et al., 2019). This study will explore what influences farmers' intention to start and to continue adopting CSA technologies for coffee.

Earlier CSA adoption studies focussed on either one or a combination of only a few CSA technologies (Diro et al., 2022b; Wiredu et al., 2015). Moreover, CSA technologies are complementary and can be used interchangeably and/or conjunctively (i.e. compost can be used as mulch and as manure), calling for bundled agricultural technologies (Rajendran et al., 2016), whereby technologies are chosen simultaneously (Fleischer et al., 2011). Positive effects of bundling CSA technologies were reported for net farm income increase (Teklewold et al., 2013), adaptive capacity (Fleischer et al., 2011; Nakabugo et al., 2019; Rajendran et al., 2016), profit maximization, and risk management (Foster & Rosenzweig, 2010; Kangogo et al., 2021) and more sustainable farming systems. For example, intensification of coffee systems with shade trees has been found to be more sustainable compared to coffee systems without intensification (Bellamy, 2013). As CSA and SI are complementary in nature, the implementation of integrated CSA technologies is also a crucial pathway to sustainable agricultural intensification (Ajibade et al., 2023; Sebatta et al., 2019) enabling the use of existing farmland while at the same time contributing to climate change mitigation, adaptation, resilience and food security (Ajibade et al., 2023; Campbell et al., 2014; Rajendran et al., 2016). Thus, CSA is not a single specific agricultural technology or practice that can be universally applied, and so multiple CSA technologies should be considered (Diro et al., 2022b; Fleischer et al., 2011; Rajendran et al., 2016). This is with the assumption that there is a substantial likelihood that usually some basic management technologies are already being implemented (Miller et al., 2017). As coffee is a crop that many farmers have grown for several years, the majority of the farmers implement at least one or more of the CSA technologies though at varying frequencies and acreage to increase their revenues and protect their crops from the effects of climate change (UCDA, 2019a). Therefore, farmers' adoption was measured based on a set of 18 CSA technologies showing that farmers have been found to implement more than one of the recommended technologies and in cases where they only implemented a few technologies, they intend to either continue implementing these technologies or they also intend with necessary resources, to take on more practices in the near future in addition to the ones they currently implement (UCDA, 2015). As such, the non-adoption of a technology in coffee production is technology-specific. For example, a farmer may not implement a certain technology (like fertilizer application) yet at the same time he could be implementing one or a combination of other technologies (like weeding and mulching). In this case, this farmer would be an adopter for weeding and mulching but a non-adopter for fertilizer application and could have the intention to take on fertilizer application in the future (and to also continue implementing weeding and mulching). With this scenario, the non-adopters were considered in the study since the majority of the smallholder farmers only implement a few of the CSA technologies while at the same time, other CSA technologies remain unimplemented (Alemu & Dufera, 2017; Faisal Salad et al., 2021; Lin, 2009; Montagnini et al., 2011). Therefore, our study assessed farmers' adoption and continuation intentions for 18 proven CSA coffee technologies, adding to the limited and inconclusive literature on the adoption of a set of CSA technologies. These are; mechanical weeding, pruning, de-suckering, cultural pest and disease control, planting of cover crops, gap filling, stumping, intercropping with bananas, soil and water conservation, planting and management of shade trees, planting improved coffee varieties, chemical weed control, chemical pest management, chemical disease management, mulching, manure application, irrigation, and application of inorganic fertilizers (Alemu & Dufera, 2017; Faisal Salad et al., 2021; Lin, 2009; Montagnini et al., 2011).

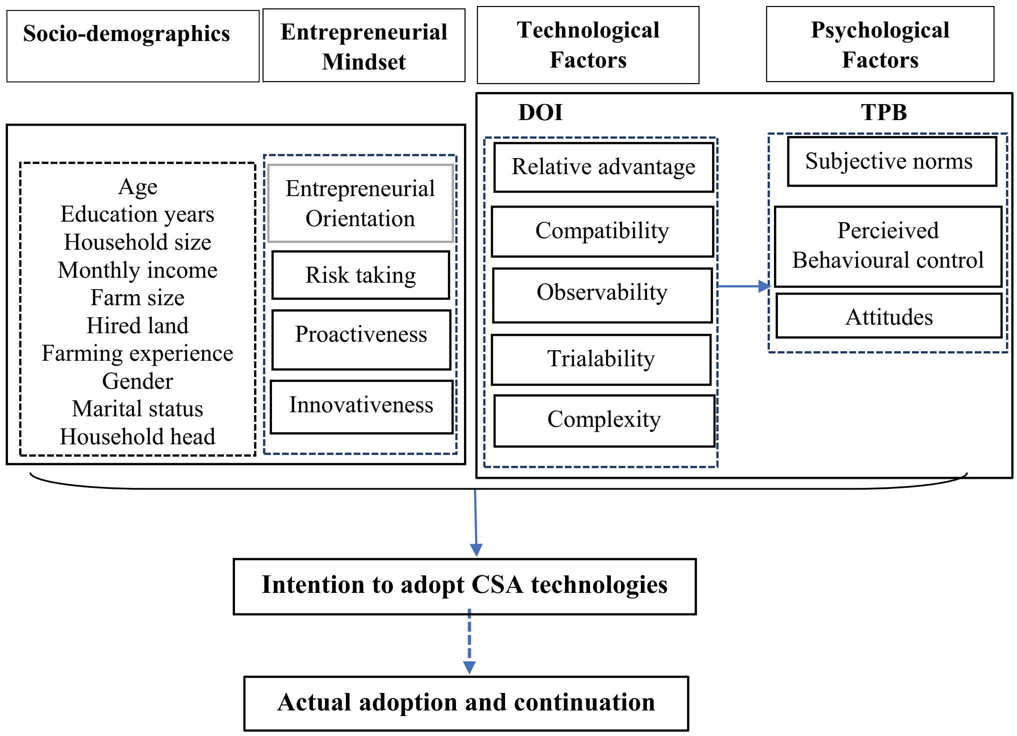
Previous research has largely elicited decisions, intentions and users' beliefs about agricultural technologies after they have already been adopted (Li et al., 2020; Nakabugo et al., 2019). Since technology adoption is a process that occurs over time, the determinants for the intention to start adopting, initial adoption and continued adoption behaviour intention may not be the same across stages and this difference remains unknown to date (Kiwanuka, 2015). Even though adoption is a prerequisite for usage, factors that affect adoption may influence or not influence the later decisions to continue using the innovation (Karahanna et al., 1999). In the context of long-term resilience to climate change, sustained/continued use of CSA technologies is more important than initial adoption (Karahanna et al., 1999). Identification of these pre-adoption conditions and their comparison to post-adoption criteria remains an important but unanswered question in agricultural research (Karahanna et al., 1999). Support for such differences between adoption and usage has been provided by consumer behaviour research (Sangroya & Nayak, 2017) and cognitive dissonance theory (Harmon-Jones & Mills, 2019). According to these theories, the initial use of a product may change one's perceptions, attitudes, and needs concerning the continued use of the product. As a result, beliefs after the use of the product may not be the same as the set of beliefs that led to initial and continued adoption (Karahanna et al., 1999). Literature is scarce on the determinants of the actual usage behaviour of CSA technologies at the initial adoption stage as well as their continuation (or discontinuation). Hence, there is only anecdotal evidence of post-adoption behaviour of CSA technology, limiting a clear understanding of sustained usage among farmers (Adapa & Roy, 2017; Alemu et al., 2023). In fact, continued technology usage has been broadly studied in other fields like education (Kafyulilo et al., 2016), information technology (Fox et al., 2021), social media use (Parveen et al., 2016; Yang et al., 2012), computer use (Karahanna et al., 1999; Venkatesh et al., 2003; Workman, 2014), and mobile payment (Al-Jabri & Sohail, 2012; Yang et al., 2012), but less in the agricultural sector. It is necessary that this phenomenon be extended to the agricultural sector to better understand the determinants of CSA technology adoption in the longer term. To fill this knowledge gap, this study will not only assess the determinants of intention to start using CSA technologies but also those that determine continuation intention.

While previous research often targeted only a few adoption factors (Bro et al., 2019; Senyolo et al., 2018), farmers' adoption of agricultural innovations has been shown to depend on a multitude of factors (Engel & Muller, 2016; FAO, 2016). These could be connected to the environment, technology, policy design features, the structure of the farm, technological aspects, behavioural factors farmers' socio-economic characteristics, attitudes, and motivations (Deng et al., 2016; Luo et al., 2016). To a greater extent, socio-economic factors influencing the adoption of CSA technologies are widely studied (Nakabugo et al., 2019; Ndamani & Watanabe, 2016; Waaswa et al., 2022) unlike farmers' attitudes (Dalila et al., 2020; Mead & Irish, 2021) and entrepreneurial mindsets (Andati et al., 2022). Farmers may lack the technical awareness and capability to adopt CSA technologies or may be unable to perceive their advantages in the long term hindering continued adoption (Zerssa et al., 2021). Also, their farming structures may not be suitable for the changes, or existing policies may be inconsiderate of their needs (Pagliacci et al., 2020). Therefore, this study examines the role of various multidimensional factors encompassing farmers' attitudes, entrepreneurial mindsets, and technological attributes on farmers' intention to start and/or to continue adopting CSA technologies. Thus, it helps address the very limited research on determinants of CSA adoption and continuation in the coffee sector (Kurgat et al., 2020) and the need to better inform policy recommendations (Makate et al., 2019; Nakabugo et al., 2019).

2. Theoretical framework

As the fundamental reasons behind technology use have often been difficult to conceptualize, despite the prevalence of technology in society, even specific factors which influence or predict future use

Figure 1. The theoretical framework for adoption and continuation intention of CSA technologies (own compilation).



remain contentious (Ding et al., 2012; Shaw et al., 2018). From a theoretical perspective, Rogers (Tran et al., 2017) stipulates that the intention to adopt technologies is a complex phenomenon requiring a complex decision-making process (Rogers, 2003) This occurs rather as a voluntary behaviour based on one's intention (Glanz et al., 2015), which results from a combination of factors like attitudes (Ajzen, 2011; Rogers, 2003) and an evaluation of the innovation itself (Rogers, 2003), such as the technology benefits, training, demonstration, and ease of use (Maina et al., 2020; Senyolo et al., 2021).

However, there is still a scarcity of studies that incorporate a diversity of theoretical factors that influence both technology adoption intention and continued use by smallholder farmers in developing contexts (Brown et al., 2018; Jassogne et al., 2017). More often the existing studies have shown that financial support through specific policy measures is insufficient for inducing CSA implementation (Darragh & Emery, 2018; Inman et al., 2018), but rather, non-financial aspects, such as technical and management considerations, policy design factors, technological and psychological factors may also act as adoption barriers (Pagliacci et al., 2020). For example, in Uganda, the slow implementation of CSA technologies was linked to limited technical capacity (Ampaire et al., 2017; Bunn et al., 2019; Zerssa et al., 2021). Regarding psychological and sociological determinants, researchers have found that attitude, social norms, personal efficacy, and perceived behavioural control play a significant role in adopting sustainable practices (Zeweld et al., 2017). Furthermore, knowledge of the technologies' strategic incentives and value configurations influences technology uptake at the farm level (Habjan & Pucihar, 2017; Tageo et al., 2020). In addition, farmers' entrepreneurial mindset and their firms' business model (Groot et al., 2019) can also play a crucial role. This also highlights the role played by farmers' entrepreneurial mindsets, motivations, and attitudes in sustainable CSA technology adoption.

Through the evaluation of previous theoretical models for technology adoption, this study proposes a combination of theories to understand adoption intention as well as the continued use of CSA technologies. Existing models of technology use posit that behaviour is consciously driven by beliefs, attitudes, and other evaluative assessments such as "performance expectancy" (Venkatesh et al., 2003). As the applications of studying technology use span widely, there has been a shift in the literature from measuring technology adoption to measuring technology use (Ding et al., 2012). Often, the continued use of technology is seen as an extension of the adoption process, suggesting both adoption and post-adoption behaviours can be measured using the same variables (Venkatesh & Thong, 2012). The most popular theory that predicts technology adoption and future use is the Technology Acceptance Model (TAM) (Marangunic & Ve Granic, 2014; Wu & Chen, 2017), which contains several variables such as perceived usefulness, perceived ease of use, external variables, attitude, and behavioural intention as precursors of technology adoption and use (Marangunic & Ve Granic, 2014). A person's attitude towards a technology before its adoption is often influenced by perceptions of usefulness, ease of use, result demonstrability, visibility, and trialability, whereas attitudes after adoption are influenced by instrumental beliefs of usefulness and perceptions of image enhancements (Karahanna et al., 1999; Moons et al., 2022). As such, it appears that continued technology use is not just a continuation of technology adoption, but a phenomenon within itself. This called for the need to extend the original TAM to better measure adoption and continued use (Ramos de Luna et al., 2016; Tsai et al., 2016), e.g., with components of other models of innovation adoption, particularly the Diffusion Of Innovations (DOI) Theory (Rogers, 2003) and the Theory of Planned Behaviour (TPB) (Ajzen, 2011). As such, several studies have primarily used the DOI theory and behavioural models, particularly the TPB, to understand the factors that explain the adoption and continued use of agricultural technologies (Deressa et al., 2009; Ndamani & Watanabe, 2016). Both theories have been used extensively and have proven successful in predicting farmers' motivation towards adopting agricultural technologies (Deressa et al., 2009; Ndamani & Watanabe, 2016). These theories also offer an understanding of the relationship people have with technologies which have become increasingly important (Shaw et al., 2018) and also provide a helpful analytical framework to explain behaviours by human beings (Inman et al., 2018). The TPB is concerned with behaviour-related variables, precisely *attitudes* which is a mindset or a tendency to act in a particular way due to both an individual's experience and personality (Ajzen, 2011; Pickens, 2005), *subjective norms* which represent the overall degree and direction of social influence felt by a person when deciding what action to enact (Etcheverry & Agnew, 2004), and *perceived behavioural control* which deals with a combination of the ease or difficulty of performing a behaviour and the extent to which performance is up to the technology adopter (Ajzen, 1991, 2011; Karahanna et al., 1999). On the other hand, in the DOI theory, the attitude towards and the adoption intention and continuous use of an innovation is influenced by five factors: *the perceived relative advantage* of the innovation which is the degree to which the adopter believes that using the innovation will provide benefits that surpass those of existing technologies in terms of satisfaction, performance, convenience, and economic benefits; *the perceived compatibility* of the innovation with the adopter's existing values, experiences and needs; the *perceived simplicity* (lack of complexity) with which the adopter believes that the innovation will not be difficult to understand and its use will be effortless; *the perceived trialability* which is the degree to which the innovation can be experienced on a limited basis, and *the perceived observability* which is the degree to which the results of an innovation are visible to adopters as technology attributes that typically influence innovation uptake (Rogers, 2003). The presence of the three TPB and five DOI factors (in positive) highlighted above, is expected to have a significant positive influence on the technology adoption decision while the reverse effect (or absence) of these factors could lead to non-adoption of technologies (Ajzen, 2011; Rogers, 2003). For example, the more complex a technology is and the less advantageous it is over other technologies, the higher the likelihood for this technology not to be adopted by the users (Ajzen, 2011; Rogers, 2003). However, their relevance could vary during the decision to continue adopting the technologies (Taherdoost, 2018; Wu & Chen, 2017)

As adoption is a complex phenomenon, it may require a combination of theories to provide complementary perspectives and hence more robust outcomes and better explanatory power (Oliveira & Martins, 2011; Samaradiwakara & Gunawardena, 2014). In addition to the TPB (Ajzen, 1991) and DOI (Rogers, 1995), other theories like the theory of Entrepreneurial Orientation (EO) can be linked to innovation adoption (Anderson et al., 2015a; Chatterjee et al., 2020), but these have only received limited attention in a farmer context. Research on the role of entrepreneurial mindsets, through EO, as potential determinants of intention to adopt technologies, is relatively novel (Dias et al., 2019; Passarelli et al., 2021), as shown for protein-rich crops in Europe (Suvanto et al., 2020). As the implementation of CSA technologies requires the farmers' ability to utilize a combination of key resources (Cinner et al., 2018) including land, labour, and capital (Amadu et al., 2020), a farmer's entrepreneurial mindset to (re)combine these resources is considered important to stimulate uptake of these technologies (Dias et al., 2019; Kangogo et al., 2021; Passarelli et al., 2021). Here, an entrepreneurial mindset is measured based on farmers' EO (Dias et al., 2019; Pindado Tapia & Sánchez García, 2017). EO captures an organization's strategy-making practices, managerial philosophies, and firm behaviours that are entrepreneurial (Anderson et al., 2015b). EO consists of three dimensions: risk-taking, innovativeness, and proactiveness as was first conceptualized by Miller, (1983) and frequently used by other researchers (Miler et al., ,2017; Suvanto et al., 2020). In this case, farmers who are innovative, proactive, and risk-takers are expected to adopt agricultural technologies more quickly than their counterparts (Pindado Tapia & Sánchez García, 2017; Suvanto et al., 2020) and likewise continue using these technologies in the long run. Previous research supports the idea that risk perception or risk tolerance can also influence the adoption intention of innovations (Bocquého et al., 2014). Jassogne et al. (2017), also revealed that the level of farmers' entrepreneurism influences technology uptake. However, there is limited literature on entrepreneurship research in agricultural enterprises including coffee and the influence of entrepreneurial mindset on farmers' adoption intentions is still largely unknown (Dias et al., 2019). The present study, therefore, integrates constructs of the EO theory into a comprehensive model that also combines the constructs of the commonly applied DOI and TPB theories to derive the theoretical model for the study. Thus the current study assessed the influence of the different theoretical determinants of the three theories; DOI , TPB, and EO on both the adoption and continuation intention of CSA technologies among smallholder coffee farmers. This will fill the knowledge gap on the interplay of these determinants in the different adoption decisions.

To the best of our knowledge, this is the first study to utilize a framework (Figure 1) that combines these three highly relevant theories and applies them to address the main research questions:

(1) To what extent do farmers' psychological factors including attitudes and entrepreneurial mindsets influence farmers' adoption and continuation intention of CSA technologies?
(2) To what extent do CSA technological factors influence farmers' adoption and continuation intention of CSA technologies?

3. Materials and methods

3.1. Study participants and data collection

The study area was Luweero district which is located in Central Uganda and lies north of Kampala, between latitude 20 north of the Equator and East between 320 and 330 (UCC, , 2011). This region was chosen based on its dominant position in coffee production (Nakabugo et al., 2019; UBOS,2018aS) and because it was the first Ugandan region where CSA projects in the coffee sector were introduced (CIAT, , 2017). In the District, Robusta coffee is mainly grown since it is flat land at a mean elevation of 1135 m (low altitude) and the conditions are favourable for this coffee type (UCC, , 2011). It is one of the districts in the country that is heavily impacted by climate change (Hilary et al., 2017) yet despite several interventions, the adoption rates of CSA technologies by farmers are still low (Mulinde et al., 2021; Nakabugo et al., 2019). The current study assessed factors that could determine the farmers' intention to start adopting (take on more CSA technologies than they currently implement) and also to continue implementing those CSA technologies that they currently implement.

The eligible farmers were 18 years and above and with a minimum of 3 years of coffee cultivation as coffee matures and gives optimal yield at about 3 years (Jassogne et al., 2017). This study used a cross-sectional approach based on multi-stage sampling: purposive sampling for selecting the Luweero district due to its relevance; and secondly, simple random sampling to select two sub-counties within the district; Nakikaaka and Kyalugondo. Purposive sampling was also used in selecting a more homogenous population of smallholder farmers with similar characteristics namely, growing coffee and exposed to CSA technologies. In particular, smallholder coffee farmers who were implementing one or more of the recommended CSA technologies under the Climate Smart Investment Pathway (Jassogne et al., 2017) were selected based on a credible database obtained from coffee producer organizations in the two sub-counties. A total number of 230 coffee farmers took part in this study.

The survey structured questionnaire consisted of five sections: socio-demographics and farm characteristics, intention to start or continue adopting CSA technologies, constructs on DOI, TPB, and EO theories. The assessment of the DOI, TPB, and EO constructs used a 7-point Likert scale (1 – strongly disagree, to 7 – strongly agree) (Covin & Slevin, 1989). They were, however slightly modified to meet the Ugandan setting of coffee production. The development of the DOI part of the CSA adoption scale used different items falling into specific attributes for subscales, namely "Relative Advantage", "Compatibility", "Trialability", "Complexity", and "Observability (Rogers, 2003). The DOI constructs and its 17 items (Moore & Benbasat, 1991) were rephrased to reflect CSA technology rather than information technology. Except for relative advantage (5 items were measured), three items were used for each construct (compatibility, complexity, trialability, and Observability). Similarly, 7-point Likert scales were used to assess adoption intentions, attitudes, subjective norms, and perceived behavioural control. The original TPB constructs (adoption intentions, attitudes, subjective norms, and perceived behavioural control) (Ajzen, 2011) were adapted to CSA technologies with three items per construct. Coffee farmers' intentions to either start to adopt or continue implementing CSA technologies were assessed by their level of agreement or disagreement with the statements based on the respective scales. For EO, we employed the three dimensions (innovativeness, risk-taking, and proactiveness constructs) (Miller, 1983;).

With the help of 10 trained research assistants, data was collected from March to April 2022 using a pre-tested digitized structured questionnaire during the face-to-face interviews. Respondents were assured of the anonymity of their responses. After every interview, the completed questionnaires were immediately uploaded to the Open Data Kit server by the research assistants. The survey process adhered to the standard ethical requirements for data collection involving humans (Mandal et al., 2011). An ethical clearance certificate was obtained from the International Institute of Tropical Agriculture (IITA) Internal Review Board (IRB) per the Research Ethics Policy under the Reference number IRB/003/2022 on 13 March 2022. The respondent response rate was 100%, so the data for all 230 respondents was complete and used in the analysis and reporting.

3.2. Data analysis

The collected data was exported to the Statistical Package for Social Sciences (SPSS) version 27. Multiple-choice questions like the adoption of individual CSA technologies and EO scores were turned into dummy variables, after which composite variables were developed for the adoption of individual technologies but also for entrepreneurial orientation scale variables. Furthermore, R software version 4.0.5 was also used to analyse structural modeling (Oberski, 2014) and Confirmatory Factor Analysis (CFA) (Huang, 2017; Oberski, 2014). An explanatory research approach was used to verify the relationship between study variables and explain the reasons for an observed event. The analysis started with descriptive statistics which analysed the frequencies, proportions, mean and standard deviations of socio-demographics. Also, an analysis of the adoption pattern was carried out by classifying the CSA technologies based on the basic requirements (land, labour and capital) for their implementation (Amadu et al., 2020; Kangogo et al., 2021; Nyasimi et al., 2017) to assess the impact of production factors on coffee farmers' adoption and continuation intentions. The mean and standard deviations for each indicator item were computed and Cronbach's alpha was used to measure the internal consistency of items used for latent variables.

A Multi-group Covariance-based Structural Equation Model (SEM) type of analysis was applied to compare the predictors for the adoption among those farmers intending to start adopting CSA technologies and those who intend to continue adopting these technologies considering the two key dependent variables (the CSA technologies adoption intention and the attitude toward CSA technologies). Multi-group testing using covariance-based SEM is the most common approach used to establish measurement and structural equivalence of the model paths across groups (Chin et al., 2014; Hair et al., 2017). The SEM consisted of a measurement and structural model. 1) the *measurement model* was computed by CFA based on the maximum likelihood estimator approach, which was used to assess the validity of measures used in the study (Wang et al., 2015a; Wesana et al., 2018) and to verify the observed variables' factor structure for EO, DOI, and TPB. This generated the latent constructs as a function of the observed variables. The hypothesis that there was a link between observable variables and their underlying latent components was tested using CFA with the package “lavaan”, which was constructed under R version 4.0.5 (Oberski, 2014). The 10 latent variables with their indicator items (as observed variables) constituted the measurement model to produce factor loadings. The factor loadings were extracted from the CFA model summary and used to assess the reliability and validity of the CFA model. The Chi-square test, absolute fit indices, incremental fit indices, and parsimonious fit indices were also used to analyze the model’s Goodness of Fit (GOF). According to Hair et al. (2010), the rule of thumb for GOF is to use the Chi-square test and at least one index from each of the other groups. The factor loadings were extracted from the CFA model summary and used to assess the reliability and validity of the CFA model and to determine whether the data were suitable for SEM. Composite reliability (CR), internal consistency (Cronbach’s Alpha), and Average Variance Extracted (AVE) were used to assess the reliability of each concept in the measurement model. CR and Cronbach’s Alpha values vary from 0 to 1, with values of 0.60 and higher considered to be acceptable (Hair et al., 2010). Similarly, AVE values of 0.5 and above are acceptable (Ahmad et al., 2016). Equally, the construct validity of the measurement model was assessed using correlations and the latent exogenous constructs of 0.85, and the square root of AVE for each construct if larger than the correlation between corresponding constructs meant that the measurement model achieved discriminant validity (Ahmad et al., 2016). Following the measurement model, 2*) the structural model* was developed. This quantified the relationships between the latent constructs (Hair et al., 2010) which were later interpreted and discussed. The model’s GOF was assessed using the Chi-square ratio (CMIN/DF), absolute fit indices, incremental fit indices, parsimonious fit indices, Tucker—Lewis index (TLI), Comparative Fit Index (CFI), Standardized Root Mean Squared Residual (SRMR) and the Root Mean Square Error of Approximation (RMSEA) (Kline, 2015; Wang et al., 2015a).

4. Results

4.1. Farmers’ characteristics

The main sample characteristics are presented in Table 1. Most coffee farmers are male, married household heads with little household income. The larger number of males in our sample confirms the general gender bias reported in coffee farming (ICO, 2018). Coffee growing is generally carried out by older adults (Aguirre Cuellar et al., 2022; Ngeywo et al., 2015). The interviewed farmers owned small farm sizes which aligns with the national statistics that more than 90% of coffee farmers are

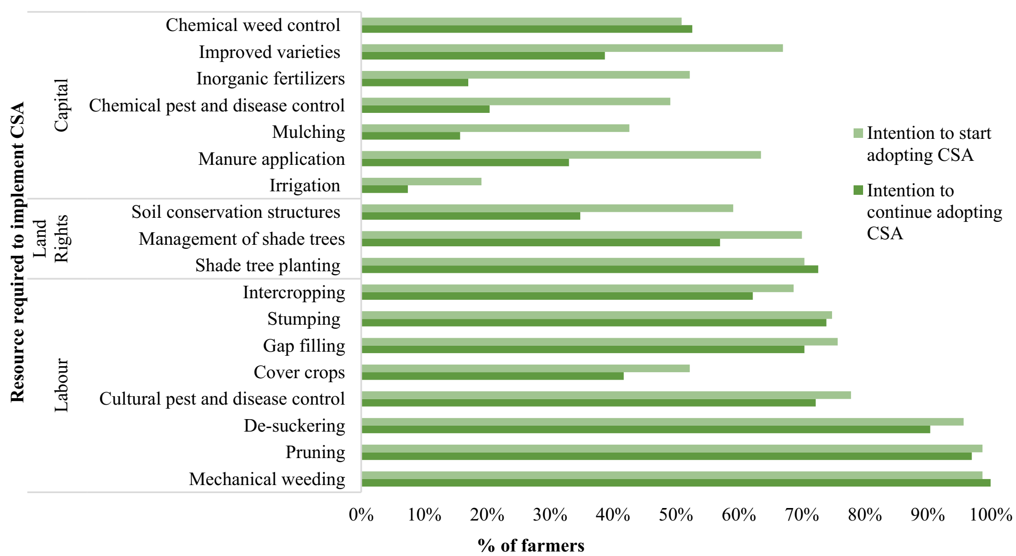
Table 1. Farmers’ socio-demographic and farm characteristics

Response	**N(%)**
Gender	
Female	74(32.20)
Male	156(67.80)
Marital Status	
Divorced/Separated	6(2.60)
Married	176(76.50)
Single	15(6.53)
Widow(er)	33(14.31)
Household Head	
Yes	195(84.80)
No	35(15.20)
Response	$\bar{X} \pm$ SD
Age (years)	52.62 ± 14.83
Years of formal education (years)	6.40 ± 4.81
Household Size	7.47 ± 4.52
Household Monthly income (USD)	90.80 ± 206.4
Farm size (ha)	1.46 ± 1.83
Hired land (ha)	0.14 ± 0.56
Agriculture experience (years)	29.45 ± 15.03

smallholders (UCDA, 2019b) with low incomes below the national poverty line (UBOS, 2018a). Furthermore, they generally had large household sizes and high agriculture and coffee farming experience. The average household size of coffee farmers was higher than the country's average (5 members) (UBOS, 2018b). Our study found that the average years of formal education was 6.40 ± 4.8 years, i.e. at least a basic primary education, which supports the prevailing evidence that the highest education level attained by most adults in Uganda is 1–7 years (UBOS, 2018a).

CSA technology adoption patterns of the farmers are presented in Figure 2. Overall, all the farmers were implementing at least one CSA technology and there was no farmer that was not implementing a CSA technology. The majority of farmers had a high intention to adopt CSA technologies that are new to them and they also intended to continue implementing those technologies they already adopted. Adoption rates are higher and more balanced for labour-intensive technologies followed by land-intensive and capital-intensive technologies. This can be attributed to the high financial needs and large household sizes among smallholder farmers (Medellín-Azuara et al., 2012; Vondolia et al., 2021) which could limit the interest in capital-intensive technologies in favour of the adoption of labour-intensive technologies respectively (Sebatta et al., 2019).

Figure 2. Farmers' adoption of CSA technologies.



4.2. Measurement and structural models

CFA was carried out to test the suitability of the core constructs of our model for SEM. The measurement model was developed to generate the latent constructs as a function of the observed variables. From the measurement model descriptives presented in Table 2, on average, the 230 respondents exhibited a modest (3.61 + 1.18) to high (5.10 + 0.94) level of agreement (based on the 7-point Likert scale) with individual items from the 9 constructs in the measurement model as indicated in Table 4. Internal consistency of constructs, measured by Cronbach's alpha, was high ranging from 0.822 to 0.963, more than the recommended cut-off threshold 0f 0.7 (Nunnally & Bernstein, 1994). From Confirmatory Factor Analysis, all items for each construct had high values of factor loadings (above 0.6), with significant associations with latent variables ($p < 0.001$). Also, the value of Cronbach Alpha for all constructs is greater than 0.60 and the Average Variance Extracted (AVE) for each construct is greater than 0.5 (Hilton et al., 2014). The GOF statistics for the measurement model were all satisfactory. The chi-square to the degree of freedom ratio was 2.01 which is satisfactory as the recommended value ranging from 1 to 3 (Wang et al., 2015b). Additionally, the results from the three dimensions were used to gauge the model's reliability; the internal consistency of the scale's items was based on Cronbach's Alpha. Composite reliability was based on the factor loading same as the Average Variance Extracted (AVE). Based on the CFA calculations, a fitting model was calculated with a probability value of 0, a CMIN/DF score of 2.01, a CFI score of 0.939, an RMSEA score of 0.066 and an SRMR score of 0.044. The GOF statistics for the measurement model were all satisfactory.

Table 2. Measurement model descriptive statistics

Construct	Mean	SD	CFA Loadings
Relative Advantage (α= 0.951)			
Practicing CSA could enable me to accomplish farm work more easily	4.91	1.22	0.879**
Practicing CSA could improve the quality of my coffee produce	4.91	1.12	0.905**
Practicing CSA could make it easier to grow coffee	4.95	1.17	0.909**
Practicing CSA could enhance my effectiveness in coffee production	4.97	1.08	0.915**
Practicing CSA could give me greater control over my coffee farm	4.89	1.22	0.850**
Compatibility (α=0.901)			
Practicing CSA matches the traditional ways of operating the coffee farm	3.26	0.94	0.939**
Practicing CSA could fit well the way I like to do farming	4.42	0.92	0.962**
Practicing CSA could fit into my farming style	4.13	1.00	0.936**
Complexity (α= 0.962)			
I believe that it is easy to practice CSA for a particular purpose	4.52	1.29	0.781**
Overall I believe that practicing CSA is easy	4.35	1.43	0.904**
Guideline for practicing CSA are easy for me	4.35	1.46	0.921**
Trialability (α=0.908)			
Before deciding on whether to practice CSA, I need to properly try them out	4.84	1.16	0.726**
It is easy for me to practice CSA if I am permitted to use it on a trial basis long enough to see what it can do	4.83	1.17	0.868**
Practicing CSA on a trial basis may be easy for me	4.92	1.15	0.804**
Observability (α= 0.965)			
CSA has been well demonstrated in my village	4.15	1.27	0.925**
People can tell that your farm has changed when you practice CSA	4.71	1.24	0.949**
Practicing CSA could improve the way my farm looks like	4.74	1.23	0.846**
Perceived Behavioural Control (α= 0.911)			
I have sufficient resources to practice CSA in part of my coffee farm next year	3.97	1.36	0.900**
I am confident that I can practice CSA in part of my coffee farm next year	3.97	1.32	0.900**
Deciding on whether to practice CSA in my coffee farm within next year is completely up to me	3.99	1.33	0.875**
Subjective Norms (α= 0.902)			
Most people who matter to me would support me to practice CSA with my coffee farm next year	5.10	0.94	0.897**
Most people whose opinion I value would approve that I practice CSA within my coffee farm next year	5.05	0.89	0.975**
Most farmers like me will practice CSA in at least part of their coffee farm next year	4.97	0.99	0.940**
Attitude (α= 0.822)			

(Continued)

Table 2. (*Continued*)

Construct	Mean	SD	CFA Loadings
Practicing CSA in part of my coffee farm next year would be advantageous	3.61	1.18	0.913**
Practicing CSA in part of my coffee farm next year is necessary	3.86	1.27	0.922**
Practicing CSA in part of my coffee farm next year is important	4.07	1.54	0.800**
Entrepreneurial Orientation (α= 0.951)			
On my farm, I prefer to follow possibilities to change practices and routines	4.23	1.49	0.8063**
On my farm, I prefer to follow high-risk farming practices	3.88	1.28	0.861**
I typically adopt an aggressive posture to maximize the possibility of exploiting potential opportunities	4.10	1.21	0.897**
My farm produced many new crops or services in the past five years	3.99	1.19	0.828**
On my farm, changes in the production system and practices have been dramatic	3.88	1.23	0.778**
We are very often among the first farms to adopt new crops and practices	3.98	1.34	0.893**
My farm typically initiates actions or practices that other farmers respond to	4.03	1.36	0.896**
Intention to adopt (α= 0.942)			
How likely is it that you will practice CSA in part of your coffee farm within next year	4.30	1.45	0.930**
I intend to practice CSA in part of my coffee farm within next year	4.23	1.41	0.950**
I may practice CSA in part of my coffee farm within next year	4.40	1.46	0.887**

N = 230; Items were measured on a 7-point Likert scale, α Cronbach's alpha, ** indicate significance at p <0.001. GOF: Chi-square (549) = 1102.133, p < 0.001; chi-square/d.f. =2.01, CFI = 0.939, TLI = 0.930, RMSEA=0.066, SRMR= 0.044.

Table 3. Construct validity of the measurement model

Construct	1	2	3	4	5	6	7	8	9	10	CR	AVE
1.Rel Advantage	**0.89**										0.951	0.796
2. Compatibility	0.44	**0.95**									0.962	0.894
3. Complexity	0.16	0.20	**0.87**								0.904	0.758
4. Trialability	0.35	0.10	0.25	**0.91**							0.843	0.642
5. Observability	0.15	0.11	0.02	0.29	**0.91**						0.934	0.824
6. Attitude	0.42	0.35	0.06	0.19	0.37	**0.88**					0.911	0.775
7.Subjective Norms	0.25	0.15	0.11	0.29	0.32	0.18	**0.93**				0.956	0.880
8.Entrepreneurial Orientation	0.42	0.17	0.33	0.70	0.10	0.16	0.27	**0.86**			0.952	0.740
9.Perceived Behavioural Control	0.60	0.23	0.35	0.75	0.22	0.25	0.31	0.80	**0.89**		0.921	0.795
10.Intetion to Adopt	0.60	0.21	0.30	0.70	0.27	0.18	0.40	0.83	0.80	**0.92**	0.945	0.852

Abbreviation: EO, Entrepreneurial Orientation. PBC, Perceived behavioural control. N =230. CR: Composite reliability, AVE: Average Variance Extracted.
Numbers in bold on the main diagonal are square roots of the AVE, others are correlation coefficients.

The construct validity of the measurement model was assessed using the correlation matrix presented in Table 3. The correlation matrix of latent exogenous constructs is all below the permissible level (0.85), and the square root of AVE (diagonal values in bold) for each construct is larger than the correlation between corresponding constructs, implying that the measurement model achieves discriminant validity (Ahmad et al., 2016). For each construct, Composite Reliability (CR) values ranged from 0.843 to 0.962 while Average Variance Extracted (AVE) values ranged from 0.642 to 0.894, higher than the acceptable level of 0.8 and 0.5, respectively (Ping, 2004). The high CR suggested and the AVE demonstrated convergent validity of constructs used in this study. In addition, the lowest square root of AVE was 0.86 in contrast to 0.35 which was the highest correlation between constructs, hence indicating that constructs are less related (i.e., discriminant validity).

As the measurement model's validity, internal consistency, reliability, factor loadings and GOF indices were satisfactory with sufficient information to consider the unidimensionality of the scales and data (Wesana et al., 2018). Therefore, the structural model was assembled for further analysis. The structural model quantified the relationships between the latent constructs (Hair et al., 2010). Table 4 shows that the model statistics of the multi-group SEM analysis sufficiently met the recommended thresholds for a fitting model (Chin et al., 2014; Hair et al., 2017).

Table 4. Model statistics for the multi-group SEM model

Statistic	Threshold	Value
CMIN/DF	1–3	2.12
TLI	≥0.90	0.912
CFI	≥0.90	0.905
RMSEA	<0.8	0.075
SRMR	<0.09	0.063
χ^2,df,p	-	2364.960, 1114, 0

A multi-group SEM estimation for the attitude toward CSA technologies and the intention to start (group 1) and to continue (group 2) adopting CSA technologies was developed, as summarized in Table 5. The R^2 values (ranging from 0.42 to 0.63) of the estimates indicate that the model predicted the outcomes well. The model's convergent validity was attained, as the construct parameter estimations are significant and coherent with the theory. Similarly, according to the GOF indices, the model fits well and achieves construct validity as specified by Hair et al. (2010).

This multi-group analysis revealed that out of the three TPB constructs, both attitude and perceived behavioural control (the stronger predictor) positively and significantly determined intention to start to adopt CSA technologies yet subjective norm was a significant hindering factor. However, only the farmers' attitude had a significant positive influence on continuation intention. Generally, the more positive a coffee farmer's attitude toward CSA technologies is, the more likely they will start and/or continue to adopt them. Additionally, all five perceived technology characteristics per the DOI model, were significant predictors for farmers' intention to start adopting the CSA technologies, with only the relationship with complexity being negative. Again, only one factor, i.e. compatibility, positively and significantly influenced continuation intention. Finally, EO was a significant, positive predictor for both adoption intention and continuation. This means that enterprising coffee farmers are more likely to start and continue adopting CSA technologies on their farms.

5. Discussion

The current study expounds on the diversity of factors that influence CSA technology adoption intention among smallholder farmers based on their attitudes and EO. It includes novel insights from cognitive traits like entrepreneurial orientation, a new concept in agricultural research.

Table 5. Multi-group covariance-based SEM parameter estimates

Adoption intention	Theory	Predictors	Coefficient	SE	Z	P value	R^2
Group 1 - Intention to start adopting CSA technologies	Theory of Planned Behaviour (TPB)	Attitude	0.09	0.036	2.511	0.012**	0.52
		Subjective Norms	−0.1	0.055	1.815	0.070*	
		Perceived Behavioural Control	1.564	0.39	3.992	0.000***	
	Diffusion Of Innovations Theory (DOI)	Relative advantage	0.264	0.08	3.516	0.000***	0.63
		Compatibility	0.592	0.13	4.458	0.000***	
		Complexity	−0.141	0.07	−2.079	0.038**	
		Trialability	0.219	0.08	2.863	0.055*	
		Observability	0.136	0.07	1.918	0.004**	
	Entrepreneurial Orientation (EO) theory	Entrepreneurial Orientation	0.919	0.54	1.696	0.090*	
Group 2 - Intention to continue adopting CSA technologies	Theory of Planned Behaviour (TPB)	Attitude	0.368	0.16	2.335	0.020**	0.42
		Subjective Norms	−0.118	0.13	0.882	0.378	
		Perceived Behavioural Control	0.337	0.25	1.333	0.183	
	Diffusion Of Innovations (DOI) Theory	Relative advantage	0.44	0.32	1.374	0.169	0.47
		Compatibility	0.246	0.12	2.016	0.044**	
		Complexity	−0.102	0.13	−0.805	0.421	
		Trialability	0.084	0.12	0.697	0.486	
		Observability	0.123	0.1	1.289	0.197	
	Entrepreneurial Orientation (EO) theory	Entrepreneurial Orientation	0.786	0.26	3.059	0.002**	

* Significant at 10% **Significant at 5% ***Significant at 1%

Examining how farmer entrepreneurial mindsets and attitudes influence CSA adoption offers a solid platform for more targeted sustainable scaling policies and intervention strategies to be designed and implemented. The results reveal that the different theoretical constructs influence the intention to start and to continue adopting CSA technologies differently. While all constructs were significant determinants of adoption intention to various degrees, only a few of these were also important for the intention to continue adopting these technologies.

5.1. Influence of different theoretical constructs on adoption intention and continuation

5.1.1. Theory of Planned Behaviour (TPB) constructs

First of all, our results are similar to several studies that point to attitude as a strong determinant of behavioural intention (Cavane & Donovan, 2011; Chuang et al., 2020). This may call for increased communication efforts to create awareness about particular perceived technology characteristics, which are critical in forming a positive attitude toward CSA adoption (Serote et al., 2021; Tama et al., 2023).

Our results indicate that perceived behavioural control is also a significant predictor of farmers' intention to start adopting CSA technologies. Coffee farmers who perceive a high level of control over CSA implementation are more likely to adopt the technology than those who believe they have little or no control. Other scholars reported that perceived control is a significant predictor of behavioural intention to adopt shade trees in coffee farms (Aguirre Cuellar et al., 2022; Daniele et al., 2017). Farmers typically argue that deploying CSA technologies on their farms is out of their control without significant support from different actors like organizations and the government to remove impediments such as a lack of improved seedlings, inadequate tools, and access to water (Covin & Slevin, 1989). It is therefore evident that a multi-stakeholder approach is key in scaling up the adoption of CSA technologies among coffee farmers.

Surprisingly, subjective norms were a key hindering factor for adoption intention but not for continuation intention. While the latter contradicts previous research (Schepers & Wetzels, 2007; Van Kleef et al., 2019), our results are consistent with respect to the negative relationship between subjective norms and intention to adopt (Sangroya & Nayak, 2017). CSA technologies will be less likely to be adopted on coffee farms if they undercut pre-existing social-cultural attachments and also suggests that social pressure will negatively impact those who might have found CSA easy to use. Agarwal, (2000) for instance, reported that mandating technology use against the explicit will of an individual may result in negative consequences. Thus, different stakeholders and policymakers promoting CSA technology adoption should stimulate the voluntary adoption of technologies among intended users. As such, there might be positive subjective norms that can support technology uptake and continuation, regardless of the hindering effect of negative subjective norms (Kim et al., 2006). In line with this, CSA technologies must be context-specific to match the social norms and must also be introduced using participatory approaches and communicated through social channels and structures, such as community leadership, for the technologies to be widely adopted (Deng et al., 2016; Taherdoost, 2018).

5.1.2. Diffusion Of Innovations (DOI) constructs

The findings of the influence of DOI constructs on adoption intention are slightly similar to the study of Karahanna et al. (1999) on information technology users, by which all five DOI constructs shaped technology pre-adoption behaviour while only a few constructs (perceived usefulness and image) influenced post-adoption behaviour. Also, Moore and Benbasat's (1991) results showed compatibility, perceived usefulness, and ease of use as the most influential for continued usage decisions. The difference in the influence of these factors on intention to start vis-à-vis continue adopting technologies can be explained in different ways as elaborated below.

Regarding relative advantage, CSA is often considered to score better in terms of economic, technical, and environmental elements compared to other agriculture technologies (Lipper et al., 2014; Waaswa et al., 2022). Specific sub-dimensions of relative advantage, such as economic profitability, low initial cost, minimal discomfort, and effort while using the innovation, have shown to be positively related to enhancing awareness and adoption of agriculture technologies (Liao & Lu, 2008; Sekabira et al., 2022). This makes relative advantage an important determinant for technology uptake but not necessarily for continuation as shown also in this study. Indeed, pre-adopters typically attach more relevance to CSA technologies over other agricultural technologies at the start of using the technology but this declines after adoption (Dercon & Christiaensen, 2011).

Trialability as a positive, significant determinant of intention to start adopting technologies means that farmers are more likely to adopt CSA technologies which they can experiment with during implementation (Kim et al., 2006). In this case, the trialability of an innovation is important in reducing risk and uncertainty about the expected consequences of using the innovation making it an important decision criterion. It provides potential adopters with a risk-free way to explore and experiment with the technology, to increase their comfort level and consequently the likelihood of longer adoption. Once an innovation is in use by someone, the relevance of trialability in determining their decision to continue using the innovation vanishes as the continued technology use is based on experience (Karahanna et al., 1999).

Similarly, the observability (visibility) of CSA technologies provides an opportunity for farmers to observe others using the technology. Such psychological or vicarious trials can be a very effective source of information for potential technology adopters. Following adoption, however, individuals acquire personal experience with the technology and consequently their sources for decision-making. As a result, the relevance of visibility in usage decisions also declines after adopting a technology (Karahanna et al., 1999) When farmers have more opportunities to see the actual technologies early enough before they use them, they can have a better understanding of CSA technologies. This raises the farmers' cognitive values including performance expectancy, effort expectancy, and subjective norms. Also, as observability increases, farmers may feel more pressure than before. This also reduces their fears of the unknown and the inability to use the technology, hence fostering the likelihood to start using the technology (Karahanna et al., 1999). In their study on teaching, Collis and Moonen (Collis & Moonen, 2001), argue that if the first experience of working with technology fits with experiences and beliefs related to the learning process, one can build up self-confidence towards the technology and will engage in technology use.

The relevance of compatibility in both intention to start and to continue adopting CSA generally implies that coffee farmers are more likely to take up and continue using the technologies that are compatible with their social norms, values, beliefs, earlier introduced ideas, current practices, and technology needs (Bryan et al., 2009). Also, when respondents believe CSA adoption is similar to existing technologies, they have a favourable attitude toward their adoption as well as continued use (Bryan et al., 2009; Karahanna et al.,). Previous scholars also found a strong impact of compatibility on adopters' technology awareness and their willingness to continue adopting the technology (Karahanna et al., 1999).

Finally, only complexity turned out to be a significant hindering factor for the intention to start adopting CSA. A similar influence of complexity or the lack of ease of use has been reported earlier (Kim & Crowston, 2011; Son & Benbasat, 2007). For example, ease of use had a greater influence on utilization for inexperienced IT users and yet it had a non-significant effect on use after 14 hours due to experience, corroborating the results of Davis et al. (1989). In this case, the lack of significance for continued adoption might be linked to the fact that after adoption, and as users gain experience with the system, the ease of use of a technology seems to be resolved and displaced by more instrumental considerations involving the efficacy of the innovation to increase performance, e.g. perceived usefulness (Bandura & Walters, 1977). When farmers perceive a technology to be relatively difficult to either understand or if its use would require them to develop new skills to actually use the technology, this would increase the rate of rejection of the technology (Rogers, 2003) and the reverse is also true.

5.1.3. Entrepreneurial Orientation (EO) constructs

EO positively and significantly influences both the intention to start and to continue adopting CSA technologies. It appears that EO is critical for identifying opportunities and overcoming financial limitations that hinder farmers from sustainably adopting CSA technologies. Earlier research suggests that entrepreneurship influences farmers' productivity and technological decisions (Dung et al., 2020). Adopting innovative technologies is not risk-free rather it enhances uncertainty (Zahra, 2018) and risk-taking is involved in the propensity to participate in innovations (Kessler & Chakrabarti, 1996). As such, being innovative, proactive, and risk-taking in farming increases technology adoption (Deka & Goswami, 2020; Pindado Tapia & Sánchez García, 2017; Suvanto et al., 2020). Furthermore, Opio, (2019) claims that innovative farmers have a competitive edge and are more sustainable in modern agriculture. As entrepreneurial orientation is more supportive of adopting new technologies and proactively responding to changing trends, the more a firm is entrepreneurially oriented, the more it will be able to compete in the industry (Deka & Goswami, 2020). From an innovativeness perspective, organizations with a great extent of EO are more "likely" to favour new ideas, technology adoption, and experimentation (Bhatia & Awasthi, 2018). This means that coffee farmers should undertake business and entrepreneurship skills training to prepare them to embrace novel technologies or ensure continued use for sustainable production in the face of climate change. This requires farmers to act entrepreneurially and accept a degree of uncertainty regarding the outcomes of CSA technologies (Deka & Goswami, 2020; Parveen et al., 2016).

Generally, the aforementioned differences in factors that determine the intention to start and to continue adopting CSA technologies as predicted by constructs of TPB, DOI and EO theories imply that a different set of strategies need to be designed to enhance uptake or continued use. As more factors determine the intention to start adopting CSA than those for continuation, interventions to enhance sustainable technology adoption should be laid early enough at the initial or convincing stage while continuous efforts should be applied along the way to achieve continued use. Pre-adoption beliefs are formed primarily based on indirect experience with the technology, linked to affect or cognition, post-adoption usage beliefs are formed based on experience (Karahanna et al., 1999; Yang et al., 2012). As it is expected that the more a technology becomes habitual through repeated use, the more the situational context will become predictive of technology use (Morris & Venkatesh, 2000; Venkatesh et al., 2003), it is important for stakeholders when designing and scaling out CSA to understand these features of both types of adopters while promoting technologies (Pathak et al., 2019).

5.2. Study limitations and future research

In terms of limitation, the study's geographical scope was rather narrow and targeted only one, large coffee-growing region in Uganda. As the adoption of farming technologies is influenced by institutional factors, land tenure, resource availability, economic, social, ecological, and climate conditions (Ajzen, 2011; FAO, 2016), it is important to interpret our results with caution and validate them in future research to strengthen generalizability. Future research should also look at the influence of variations in agroecological zones on the adoption of CSA technologies. Additionally, our study was cross-sectional in nature. Future longitudinal studies could consider investigating the adoption intensity and rate of multiple CSA technologies at different stages (recent adopters versus experienced users) over time (Kim, 2008) while utilizing, for instance, count models (Kolady et al., 2021). Alternatively, one could design a quasi-experiment to assess the factors influencing the adoption and continuation of each technology separately and jointly based on the expected random utility model approach (Cooper & Giovanni, 2002). Furthermore, the study was not able to assess how changes in EO over time can influence behavioural intention. In future research, panel data could be collected to understand the formation process of farmers' entrepreneurial behaviour and the efficacy of interventions to enhance farmers' entrepreneurial mindset. Thereby, one could evaluate adoption intention across entrepreneurship clusters. Regarding measurement, the mean values of our Likert scale items of the model constructs are relatively high. While this might point to a risk of social desirability bias (McLeod, 2008), we have attempted to minimize this through careful design and data collection. Finally, as the study focused only on attitudes, EO and technological characteristics as predictors for CSA technology adoption, it may be relevant for future research to conduct an impact analysis on adopting CSA technologies in the coffee subsector. Findings on how CSA technologies impact coffee yield, household livelihoods, and greenhouse gas emissions are important for influencing farmers' attitudes toward promoting CSA adoption and continuation (Asegid, 2020; Sun et al., 2018).

6. Conclusion and recommendations

By embracing a combination of theoretical frameworks, this study examined the influence of attitudes and EO on coffee farmers' intentions to start and continue adopting CSA technologies. Coffee farmers' intentions were found to be well predicted by TPB's psychological factors, DOI's perceived technology characteristics, and their EO. All TPB, DOI and EO constructs were significant predictors for the intention to start adopting CSA technologies. That is; perceived behavioural control, relative advantage and compatibility are the most significant positive predictors of intention to start adopting CSA technologies, attitude, observability, trialability and EO as the least significant positive predictors for behavioural intention. While subjective norms and complexity were significant hindrances to the intention to start adopting CSA technologies, only attitude, compatibility and EO are positive, significant predictors of intention to continue adopting CSA technologies.

Our findings demonstrate how non-socioeconomic determinants are crucial not only for adoption but also for continuation, despite the latter being affected by only a few indicators. As such, the theoretical frameworks played a different role in predicting both types of behaviour intentions. Thereby, our study also provided novel insights from cognitive traits like entrepreneurial orientation, a relatively new concept in agricultural research. We propose that strategies to enhance sustainable CSA technology uptake: 1) focus on raising awareness about the perceived characteristics of CSA technologies to influence positive attitudes of farmers towards adopting and sustaining CSA through well-designed extension service delivery; 2) employing a multi-stakeholder approach to remove obstacles like negative attitudes towards CSA technologies and lack of entrepreneurial orientation that hinder CSA adoption by coffee farmers; 3) providing business and entrepreneurial skills training for coffee farmers and designing extension programs to take into account variances in the farmers' entrepreneurial mindsets, and 4) be tailored to specific adoption stages considering the different role of predictors for intention to start and continue adopting CSA technologies. As such, from a practical perspective, our findings will enable private and public sector stakeholders to employ more targeted CSA design and implementation efforts towards sustainable CSA adoption and sustainable agricultural intensification.

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Data availability statement
Data will be made publicly available when the article is accepted for publication. The data will then be available in a depository at Ghent University online and physical libraries and the Consultative Group for International Agricultural Research (CGIAR) website. The data set associated with the paper can be found at https://drive.google.com/file/d/1cScrVIagktTMV_wS9_dY8OLhHfc3QHIi/view?usp=drive_link

Informed consent statement
Informed consent was obtained from all subjects involved in the study.

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All subjects gave their informed consent for inclusion before they participated in the study. The study was conducted in accordance with the Declaration of Helsinki, the protocol was approved and an ethical clearance certificate obtained from the International Institute of Tropical Agriculture (IITA) Internal Review Board (IRB) per the Research Ethics Policy under the Reference number IRB/003/2022 on 13 May 2022.

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References

Abegunde, V. O., Sibanda, M., & Obi, A. (2019). Determinants of the adoption of climate-smart agricultural practices by small-scale farming households in King Cetshwayo district Municipality, South Africa. *Sustainability*, *12*(1), 195. https://doi.org/10.3390/su12010195

Achterbosch, T. J., van Berkum, S., Meijerink, G. W., Asbreuk, H., & Oudendag, D. (2014). *Cash crops and food security: Contributions to income, livelihood risk and agricultural innovation*. LEI Wageningen UR.

Adapa, S., & Roy, S. K. (2017). Consumers' post-adoption behaviour towards internet banking: Empirical evidence from Australia. *Behaviour & Information Technology*, *36*(9), 970–983. https://doi.org/10.1080/0144929X.2017.1319498

Agarwal, R. (2000). Individual acceptance of information technologies. Framing the domains of IT management: Projecting the future through the past. *Cincinnati, OH: Pinnaflex Education Resources*, 85–104.

Aguirre Cuellar, B., Lobo, J. C., & Elcure, F. M. (2022). Shading in family coffee farms as an environmental incentive promoter for ecosystem services in Tolima, Colombia. *International Journal of Agricultural Sustainability*, *20*(6), 1–13. https://doi.org/10.1080/14735903.2022.2041234

Ahmad, S., Zulkurnain, N., & Khairushalimi, F. (2016). Assessing the validity and reliability of a measurement model in structural equation modeling (SEM). *British Journal of Mathematics & Computer Science*, *15*(3), 1–8. https://doi.org/10.9734/bjmcs/2016/25183

Ajibade, S., Simon, B., Gulyas, M., & Balint, C. (2023). Sustainable intensification of agriculture as a tool to promote food security: A bibliometric analysis. *Frontiers in Sustainable Food Systems*, *7*, 1101528. https://doi.org/10.3389/fsufs.2023.1101528

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes. Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I. (2011). The theory of planned behaviour: Reactions and reflections. *Taylor and Francis*, 26(9), 1113–1127. https://doi.org/10.1080/08870446.2011.613995

Aleminew, A., Tadesse, T., Merene, Y., Bayu, W., Dessalegn, Y., & Tejada Moral, M. (2020). Effect of integrated technologies on the productivity of maize, sorghum and pearl millet crops for improving resilience capacity to climate change effects in the dry lands of Eastern Amhara, Ethiopia. *Cogent Food & Agriculture*, *6*(1), 1728084. https://doi.org/10.1080/23311932.2020.1728084

Alemu, A., & Dufera, E. (2017). Climate smart coffee (coffea arabica) production. *American Journal of Data Mining and Knowledge Discovery*, *2*(2), 62–68.

Alemu, T., Tolossa, D., Senbeta, F., & Zeleke, T. (2023). Household determinants of continued adoption of sustainable land management measures in central Ethiopia. *Heliyon*, *9*(3), e13946. https://doi.org/10.1016/j.heliyon.2023.e13946

Al-Jabri, I. M., & Sohail, M. S. (2012). Mobile banking adoption: Application of diffusion of innovation theory. *Journal of Electronic Commerce Research*, *13*(4), 379–391.

Amadu, F. O., McNamara, P. E., & Miller, D. C. (2020). Understanding the adoption of climate-smart agriculture: A farm-level typology with empirical evidence from southern Malawi. *World Development*, *126*, 104692. https://doi.org/10.1016/j.worlddev.2019.104692

Ampaire, E. L., Jassogne, L., Providence, H., Acosta, M., Twyman, J., Winowiecki, L., & Van Asten, P. (2017). Institutional challenges to climate change adaptation: A case study on policy action gaps in Uganda. *Environmental Science & Policy*, *75*, 81–90. https://doi.org/10.1016/j.envsci.2017.05.013

Amsalu, A., & De Graaff, J. (2007). Determinants of adoption and continued use of stone terraces for soil and water conservation in an Ethiopian highland watershed. *Ecological Economics*, *61*(2–3), 294–302. https://doi.org/10.1016/j.ecolecon.2006.01.014

Andati, P., Majiwa, E., Ngigi, M., Mbeche, R., & Ateka, J. (2022). Determinants of adoption of climate smart agricultural technologies among potato farmers in Kenya: Does entrepreneurial orientation play a role? *Sustainable Technology and Entrepreneurship*, *1*(2), 100017. https://doi.org/10.1016/j.stae.2022.100017

Anderson, B. S., Kreiser, P. M., Kuratko, D. F., Hornsby, J. S., & Eshima, Y. (2015a). Eshima Y: Reconceptualizing entrepreneurial orientation. *Strategic Management Journal*, *36*(10), 1579–1596. https://doi.org/10.1002/smj.2298

Anderson, B. S., Kreiser, P. M., Kuratko, D. F., Hornsby, J. S., & Eshima, Y. (2015b). Reconceptualizing entrepreneurial orientation. *Strategic Management Journal*, *36*(10), 1579–1596. https://doi.org/10.1002/smj.2298

Anwar, M. (2019). Climate smart agriculture: Adaptation and mitigation strategies to climate change in Pakistan. In R. Shrestha & <. I. I. A. I. M. Bokhtiar (Eds.), *Climate smart agriculture: Strategies to respond climate change in South Asia* (p. 180). SAARC Agriculture Centre.

Ariani, M., Hervani, A., Setyanto, P. (2018). Climate smart agriculture to increase productivity and reduce greenhouse gas emission–a preliminary study. *Proceedings of the IOP Conference Series: Earth and Environmental Science: 2018*, Central Java-Indonesia (p. 012024). IOP Publishing.

Asegid, A. (2020). Impact of climate change on production and diversity of coffee (coffea arabica L.) in Ethiopia. *International Journal Research Studies Science Engineering Technology*, *7*(8), 31–38. https://www.ijrsset.org/pdfs/v7-i8/5.pdf

Atsiaya, G. O., Gido, E. O., & Waluse Sibiko, K. (2023). Uptake of climate-smart agricultural practices among smallholder sorghum farmers in Busia County, Kenya. *Cogent Food & Agriculture*, *9*(1), 2204019. https://doi.org/10.1080/23311932.2023.2204019

Aydinalp, C., & Cresser, M. S. (2008). The effects of global climate change on agriculture. *American-Eurasian Journal of Agricultural & Environmental Sciences*, *3*(5), 672–676.

Bandura, A., & Walters, R. H. (1977). *Social learning theory*. Englewood cliffs Prentice Hall.

Bellamy, A. S. (2013). Banana production systems: Identification of alternative systems for more sustainable production. *Ambio*, *42*(3), 334–343. https://doi.org/10.1007/s13280-012-0341-y

Bhatia, M. S., & Awasthi, A. (2018). Assessing relationship between quality management systems and business performance and its mediators: SEM approach. *International Journal of Quality & Reliability Management*, *35*(8), 1490–1507. https://doi.org/10.1108/IJQRM-05-2017-0091

Bocquého, G., Jacquet, F., & Reynaud, A. (2014). Expected utility or prospect theory maximisers? Assessing farmers' risk behaviour from field-experiment data. *European Review of Agricultural Economics*, *41*(1), 135–172. https://doi.org/10.1093/erae/jbt006

Branca, G., Braimoh, A., Zhao, Y., Ratii, M., & Likoetla, P. (2021). Are there opportunities for climate-smart agriculture? Assessing costs and benefits of sustainability investments and planning policies in Southern Africa. *Journal of Cleaner Production*, *278*, 123847. https://doi.org/10.1016/j.jclepro.2020.123847

Bro, A. S., Clay, D. C., Ortega, D. L., & Lopez, M. C. (2019). Determinants of adoption of sustainable production practices among smallholder coffee producers in Nicaragua. *Environment Development and Sustainability*, *21*(2), 895–915. https://doi.org/10.1007/s10668-017-0066-y

Brown, S. E., Miller, D. C., Ordonez, P. J., & Baylis, K. (2018). Evidence for the impacts of agroforestry on agricultural productivity, ecosystem services, and human well-being in high-income countries: A systematic map protocol. *Environmental Evidence*, *7*(1), 24. https://doi.org/10.1186/s13750-018-0136-0

Bryan, E., Deressa, T. T., Gbetibouo, G. A., & Ringler, C. (2009). Adaptation to climate change in Ethiopia and South Africa: Options and constraints. *Environmental Science & Policy*, *12*(4), 413–426. https://doi.org/10.1016/j.envsci.2008.11.002

Bunn, C., Lundy, M., Läderach, P., Fernández Kolb, P., Castro-Llanos, F. (2019). Climate-smart coffee in Uganda.

Campbell, B. M., Thornton, P., Zougmoré, R., Van Asten, P., & Lipper, L. (2014). Sustainable intensification: What is its role in climate smart agriculture? *Current Opinion in Environmental Sustainability*, *8*, 39–43. https://doi.org/10.1016/j.cosust.2014.07.002

Cavane, E., & Donovan, C. (2011). Farmers' attitude and adoption of improved maize varieties and chemical fertilizers in Mozambique. *Journal of International Agricultural and Extension Education*, *11*(1). https://doi.org/10.5191/jiaee.2011.18301

Chandra, A., Dargusch, P., McNamara, K. E., Caspe, A. M., & Dalabajan, D. (2017). A study of climate-smart farming practices and climate-resiliency field schools in Mindanao, the Philippines. *World Development*, *98*, 214–230. https://doi.org/10.1016/j.worlddev.2017.04.028

Chatterjee, S., Gupta, S. D., & Upadhyay, P. (2020). Technology adoption and entrepreneurial orientation for rural women: Evidence from India. *Technological Forecasting and Social Change*, *160*, 120236. https://doi.org/10.1016/j.techfore.2020.120236

Chemeda, B. A., Wakjira, F. S., & Hizikias, E. B. (2022). Tree diversity and biomass carbon stock analysis along altitudinal gradients in coffee-based agroforestry system of Western Ethiopia. *Cogent Food & Agriculture*, *8*(1), 2123767. https://doi.org/10.1080/23311932.2022.2123767

Chin, W. W., Mills A. M., Steel D. J., & and Schwarz A. (2014). Multi-group invariance testing: An illustrative comparison of PLS permutation and covariance-based SEM invariance analysis. In M. Skipper (Ed.), *The multiple facets of partial least squares and related Methods: PLS* (pp. 267–284). Springer

Chuang, J.-H., Wang, J.-H., & Liou, Y.-C. (2020). Farmers' knowledge, attitude, and adoption of smart agriculture technology in Taiwan. *International Journal of Environmental Research and Public Health*, *17*(19), 7236. https://doi.org/10.3390/ijerph17197236

CIAT: Climate-Smart Agriculture in Uganda. (2017).

Cinner, J. E., Adger, W. N., Allison, E. H., Barnes, M. L., Brown, K., Cohen, P. J., Gelcich, S., Hicks, C. C., Hughes, T. P., Lau, J., Marshall, N. A., & Morrison, T. H. (2018). Building adaptive capacity to climate change in tropical coastal communities. *Nature Climate Change*, *8*(2), 117–123. https://doi.org/10.1038/s41558-017-0065-x

Collis, B., & Moonen, J. (2001). *Flexible learning in a digital world: Experiences and expectations*. Psychology press.

Cooper, J., Giovanni, S.: Farmer premiums for the voluntary adoption of conservation plans, Nota di Lavoro. No 272002, Fondazione Eni Enrico Mattei (FEEM), 2002.

Covin, J. G. S., & Slevin, D. P. (1989). Strategic management of small firms in hostile and benign environments. *Strategic Management Journal*, *10*(1), 75–87. https://doi.org/10.1002/smj.4250100107

Dalaa, M. A., Deffor, E. W., Kofituo, R. K., Asare, R. (2020). Adoption of climate-smart cocoa practices in the adjust and cope climatic impact zones of Ghana.

Dalila, L., Jaafar, H., Aziz, N., & Afthanorhan, A. (2020). The mediating effect of personal values on the relationships between attitudes, subjective norms, perceived behavioral control and intention to use. *Management Science Letters*, *10*(1), 153–162. https://doi.org/10.5267/j.msl.2019.8.007

Daniele, V., Viaggi, D., & Raggi, M. (2017). Integrating spatial econometric information and optimisation models to improve agri-Environmental payment design: A resource allocation model for emilia-Romagna (Italy). *Agricultural Economics Review*, *18*(2), 40–59.

Darragh, H. S., & Emery, S. B. (2018). What can and can't crowding theories tell us about farmers''Environmental'Intentions in post-agri-Environment scheme contexts? *Sociologia ruralis*, *58*(2), 370–391. https://doi.org/10.1111/soru.12159

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

Deka, N., & Goswami, K. (2020). Organic cultivation and farm entrepreneurship: A case of small tea growers in rural Assam, India. *Agroecology & Sustainable Food Systems*, 44(4), 446–466. https://doi.org/10.1080/21683565.2019.1646373

Deng, J., Sun, P., Zhao, F., Han, X., Yang, G., & Feng, Y. (2016). Analysis of the ecological conservation behavior of farmers in payment for ecosystem service programs in eco-environmentally fragile areas using social psychology models. *Science of the Total Environment*, *550*, 382–390. https://doi.org/10.1016/j.scitotenv.2016.01.152

Dercon, S., & Christiaensen, L. (2011). Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. *Journal of Development Economics*, *96*(2), 159–173. https://doi.org/10.1016/j.jdeveco.2010.08.003

Deressa, T. T., Hassan, R. M., Ringler, C., Alemu, T., & Yesuf, M. (2009). Determinants of farmers' choice of adaptation methods to climate change in the Nile Basin of Ethiopia. *Global Environmental Change*, *19*(2), 248–255. https://doi.org/10.1016/j.gloenvcha.2009.01.002

Dias, C. S., Rodrigues, R. G., & Ferreira, J. J. (2019). Agricultural entrepreneurship: Going back to the basics. *Journal of Rural Studies*, *70*, 125–138. https://doi.org/10.1016/j.jrurstud.2019.06.001

Ding, Y., Chai, K.-H., Ng, G. (2012). Continued use of information technology: A synthesis and future directions. In: *2012 International Joint Conference on Service Sciences: 2012* Singapore: IEEE; 206–210.

Diro, S., Tesfaye, A., & Erko, B. (2022a). Determinants of adoption of climate-smart agricultural technologies and practices in the coffee-based farming system of Ethiopia. *Agriculture & Food Security*, *11*(1), 1–14. https://doi.org/10.1186/s40066-022-00385-2

Diro, S., Tesfaye, A., & Erko, B. (2022b). Determinants of adoption of climate-smart agricultural technologies and practices in the coffee-based farming system of Ethiopia. *Agriculture & Food Security*, *11*(1), 42. https://doi.org/10.1186/s40066-022-00385-2

Djufry, F., Wulandari, S., & Villano, R. (2022). Climate smart Agriculture implementation on coffee smallholders in Indonesia and strategy to accelerate. *Land*, *11*(7), 1112. https://doi.org/10.3390/land11071112

Dung, T. Q., Bonney, L. B., Adhikari, R. P., & Miles, M. P. (2020). Entrepreneurial orientation, knowledge acquisition and collaborative performance in agri-food value-chains in emerging markets. *Supply Chain Management: An International Journal*, *25*(5), 521–533. https://doi.org/10.1108/SCM-09-2019-0327

Engel, S., & Muller, A. (2016). Payments for environmental services to promote “climate-smart agriculture”? Potential and challenges. *Agricultural Economics*, *47* (S1), 173–184. https://doi.org/10.1111/agec.12307

Etcheverry, P. E., & Agnew, C. R. (2004). Subjective norms and the prediction of romantic relationship state and fate. *Personal Relationships*, *11*(4), 409–428. https://doi.org/10.1111/j.1475-6811.2004.00090.x

Faisal Salad, A., Zziwa, S., Talengera, D., Nabatanzi, L., Makumbi, O., Najjuma, V., & Nafula, M. (2021). Adoption intensity of climate smart agricultural practices in arabica coffee production in Bududa District. *International Journal of Multidisciplinary Research Updates*, *1*(1), 16–25. https://doi.org/10.53430/ijmru.2021.1.1.0037

FAO. (2016). A dynamic analysis of resilience in Uganda ESA Working Paper, 16, 36.

FAOSTAT. (2018). Disponível em: http://www.fao.org/faostat/en/#home. *Acesso em*. 30.

Fleischer, A., Mendelsohn, R., & Dinar, A. (2011). Bundling agricultural technologies to adapt to climate change. *Technological Forecasting and Social Change*, *78*(6), 982–990. https://doi.org/10.1016/j.techfore.2011.02.008

Foster, A. D., & Rosenzweig, M. R. (2010). Microeconomics of technology adoption. *Annual Review of Economics*, *2*(1), 395–424. https://doi.org/10.1146/annurev.economics.102308.124433

Fox, G., Mooney, J., Rosati, P., & Lynn, T. (2021). AgriTech innovators: A study of initial adoption and continued use of a mobile digital platform by family-operated farming enterprises. *Agriculture*, *11*(12), 1283. https://doi.org/10.3390/agriculture11121283

Glanz, K., Rimer, B. K., & Viswanath, K. (2015). *Health behavior: Theory, research, and practice*. John Wiley & Sons.

Groot, A., Bolt, J., Jat, H. S., Jat, M. L., Kumar, M., Agarwal, T., & Blok, V. (2019). Business models of SMEs as a mechanism for scaling climate smart technologies: The case of Punjab, India. *Journal of Cleaner Production*, *210*, 1109–1119. https://doi.org/10.1016/j.jclepro.2018.11.054

Habjan, K. B., & Pucihar, A. (2017). The importance of business model factors for cloud computing adoption: Role of previous experiences. *Organizacija*, *50* (3), 255–272. https://doi.org/10.1515/orga-2017-0013

Hair, J. F., Jr., Babin, B. J., & Krey, N. (2017). Covariance-based structural equation modeling in the journal of advertising: Review and recommendations. *Journal of Advertising*, *46*(1), 163–177. https://doi.org/10.1080/00913367.2017.1281777

Hair, J. F. J., William, C., Barry, J. B., & Rolph, E. A. (2010). *Multivariate data analysis* (Seventh ed.). Pearson Prentice Hall.

Harmon-Jones, E., Mills, J. (2019). An introduction to cognitive dissonance theory and an overview of current perspectives on the theory.

Hilary, R. S., Sseguya, H., Kibwika, P., & Yildiz, F. (2017). Information quality, sharing and usage in farmer organizations: The case of rice value chains in Bugiri and Luwero Districts, Uganda. *Cogent Food & Agriculture*, *3*(1), 1350089. https://doi.org/10.1080/23311932.2017.1350089

Hilton, R. P., Isabella, M., & Charlotte, B. (2014). SPSS Explained. In D., Daniel (Ed.), *Routledge* (2nd ed., p. 386). Routledge. https://doi.org/10.4324/9781315797298.

Huang, F. L. (2017). Conducting multilevel confirmatory factor analysis using R. [Unpublished Manuscript].

ICO. (2018). *Gender equality in coffee sector*. (2018). https://www.ico.org/documents/cy2017-18/icc-122-11e-gender-equality.pdf

Inman, A., Winter, M., Wheeler, R., Vrain, E., Lovett, A., Collins, A., Jones, I., Johnes, P., & Cleasby, W. (2018). An exploration of individual, social and material factors influencing water pollution mitigation behaviours within the farming community. *Land Use Policy*, *70*, 16–26. https://doi.org/10.1016/j.landusepol.2017.09.042

Jassogne L., Mukasa D., Bukomeko H., Kemigisha E., Kirungi D., Giller O., & , and Van Asten P. (2017). *The Climate Smart Investment Pathway Approach and the Farmer Segmentation Tool CCAFS Info Note*. CCAFS Info Note. International Institute of Tropical Agriculture (IITA). https://cgspace.cgiar.org/handle/10568/80747

Kafyulilo, A., Fisser, P., & Voogt, J. (2016). Factors affecting teachers' continuation of technology use in teaching. *Education and Information Technologies*, *21* (6), 1535–1554. https://doi.org/10.1007/s10639-015-9398-0

Kakraliya, S. K., Jat, H. S., Sapkota, T. B., Singh, I., Kakraliya, M., Gora, M. K., Sharma, P. C., & Jat, M. L. (2021). Effect of climate-smart agriculture practices on climate change adaptation, greenhouse gas mitigation and economic efficiency of rice-wheat system in India. *Agriculture*, *11*(12), 1269. https://doi.org/10.3390/agriculture11121269

Kangogo, D., Dentoni, D., & Bijman, J. (2021). Adoption of climate-smart agriculture among smallholder farmers: Does farmer entrepreneurship matter? *Land Use Policy*, *109*, 109. https://doi.org/10.1016/j.landusepol.2021.105666

Karahanna, E., Straub, D. W., & Chervany, N. L. (1999). Information technology adoption across time: A cross-sectional comparison of pre-adoption and post-adoption beliefs. *MIS Quarterly*, *23*(2), 183–213. https://doi.org/10.2307/249751

Karlsson, N. P., Halila, F., Mattsson, M., & Hoveskog, M. (2017). Success factors for agricultural biogas production in Sweden: A case study of business model innovation. *Journal of Cleaner Production*, *142*, 2925–2934. https://doi.org/10.1016/j.jclepro.2016.10.178

Kessler, E. H., & Chakrabarti, A. K. (1996). Innovation speed: A conceptual model of context, antecedents, and outcomes. *The Academy of Management Review*, *21*(4), 1143–1191. https://doi.org/10.2307/259167

Kim, B. K. (2008). Understanding the difference in adoption and continued usage of mobile data services. *PACIS 2008 Proceedings* Suzhou, China. 271.

Kim, Y., & Crowston, K. (2011). Technology adoption and use theory review for studying scientists' continued use of cyber-infrastructure. *Proceedings of the American Society for Information Science and Technology*, *48*(1), 1–10.

Kim, D. R., Kim, B. G., Aiken, M. W., & Park, S. C. (2006). The influence of individual, task, organizational support, and subject norm factors on the adoption of groupware. *Academy of Information and Management Sciences Journal*, *9*(2), 93–110. https://www.proquest.com/scholarly-journals/influence-individual-task-organizational-support/docview/214623140/se-2?accountid=11077

Kiwanuka, A. (2015). Acceptance process: The missing link between UTAUT and diffusion of innovation theory. *American Journal of Information Systems*, *3*(2), 40–44.

Kline, R. B. (2015). *Principles and practice of structural equation modeling*. Guilford publications.

Kolady, D. E., Van der Sluis, E., Uddin, M. M., & Deutz, A. P. (2021). Determinants of adoption and adoption intensity of precision agriculture technologies: Evidence from South Dakota. *Precision Agriculture*, *22*(3), 689–710. https://doi.org/10.1007/s11119-020-09750-2

Kuma, T., Dereje, M., Hirvonen, K., & Minten, B. (2019). Cash crops and food security: Evidence from Ethiopian smallholder coffee producers. *The Journal of Development Studies*, *55*(6), 1267–1284. https://doi.org/10.1080/00220388.2018.1425396

Kurgat, B. K., Lamanna, C., Kimaro, A., Namoi, N., Manda, L., & Rosenstock, T. S. (2020). Adoption of climate-smart agriculture technologies in Tanzania. *Frontiers in Sustainable Food Systems*, 4(55). https://doi.org/10.3389/fsufs.2020.00055

Lamanna, C., Steward, P., Kamau, H. N., Nowak, A. C., Rosenstock, T. S. (2020). Data Atlas for Climate-Smart Agriculture in KENYA.

Liao, H.-L., & Lu, H.-P. (2008). The role of experience and innovation characteristics in the adoption and continued use of e-learning websites. *Computers & Education*, *51*(4), 1405–1416. https://doi.org/10.1016/j.compedu.2007.11.006

Li, W., Clark, B., Taylor, J. A., Kendall, H., Jones, G., Li, Z., Jin, S., Zhao, C., Yang, G., Shuai, C., Cheng, X., Chen, J., Yang, H., & Frewer, L. J. (2020). A hybrid modelling approach to understanding adoption of precision agriculture technologies in Chinese cropping systems. *Computers and Electronics in Agriculture*, *172*, 105305. https://doi.org/10.1016/j.compag.2020.105305

Lin, B. B. (2009). Coffee (café arabica var. Bourbon) fruit growth and development under varying shade levels in the Soconusco region of Chiapas, Mexico. *Journal of Sustainable Agriculture*, *33*(1), 51–65. https://doi.org/10.1080/10440040802395007

Lipper, L., Thornton, P., Campbell, B. M., Baedeker, T., Braimoh, A., Bwalya, M., Caron, P., Cattaneo, A., Garrity, D., Henry, K., Hottle, R., Jackson, L., Jarvis, A., Kossam, F., Mann, W., McCarthy, N., Meybeck, A., Neufeldt, H. … Tibu, A. (2014). Climate-smart agriculture for food security. *Nature Climate Change*, *4*(12), 1068–1072. https://doi.org/10.1038/nclimate2437

Luo, L., Qin, L., Wang, Y., & Wang, Q. (2016). Environmentally-friendly agricultural practices and their acceptance by smallholder farmers in China—A case study in Xinxiang County, Henan Province. *Science of the Total Environment*, *571*, 737–743. https://doi.org/10.1016/j.scitotenv.2016.07.045

Mahato, A. (2014). Climate change and its impact on agriculture. *International Journal of Scientific and Research Publications*, 4(4), 1–6.

Maina, K., Ritho, C., Lukuyu, B. A., & Rao, E. (2020). Socio-economic determinants and impact of adopting climate-smart Brachiaria grass among dairy farmers in Eastern and Western regions of Kenya. *Heliyon*, *6*(6), e04335. https://doi.org/10.1016/j.heliyon.2020.e04335

Makate, C., Makate, M., Mango, N., & Siziba, S. (2019). Increasing resilience of smallholder farmers to climate change through multiple adoption of proven climate-smart agriculture innovations. Lessons from Southern Africa. *Journal of Environmental Management*, *231*, 858–868. https://doi.org/10.1016/j.jenvman.2018.10.069

Mandal, J., Acharya, S., & Parija, S. C. (2011). Ethics in human research. *Tropical Parasitology*, *1*(1), 2. https://doi.org/10.4103/2229-5070.72105

Marangunic, N., & Ve Granic, A. (2014). Technology Acceptance Model: A Literature Review from 1986 to 2013. *Univ Access Inf Soc*, *14*, 81–95. https://doi.org/10.1007/s10209-014-0348-1

McLeod, S. (2008). Likert scale Likert scale examples how can you analyze data from a Likert scale? *Simply Psychology*, 1–3. https://www.simplypsychology.org/likert-scale.html

Mead, M. P., & Irish, L. A. (2021). Intraindividual variability of sleep opportunity attitudes, perceived norms, perceived behavioral control, and intentions. *Annals of Behavioral Medicine: A Publication of the Society of Behavioral Medicine*, *55*(7), 693–697. https://doi.org/10.1093/abm/kaaa112

Medellín-Azuara, J., Howitt, R., & Harou, J. (2012). Predicting farmer responses to water pricing, rationing and subsidies assuming profit maximizing investment in irrigation technology. *Agricultural Water Management*, *108*, 73–82. https://doi.org/10.1016/j.agwat.2011.12.017

Miller, D. (1983). The correlates of entrepreneurship in three types of firms. *Management Science*, *29*(7), 770–791. https://doi.org/10.1287/mnsc.29.7.770

Miller, N. J., Griffin, T., Bergtold, J., Sharda, A., & Ciampitti, I. (2017). Farmers' Adoption Path of Precision Agriculture Technology. *Advances in Animal Biosciences*, *8*(2), 708–712. https://doi.org/10.1017/S2040470017000528

Montagnini, F., Francesconi, M., & Rossi, E. (2011). Payments for environmental services in Latin America as a tool for restoration and rural development. *Ambio*, *40*(3), 285–297. https://doi.org/10.1007/s13280-010-0114-4

Moons, I., De Pelsmacker, P., Pijnenburg, A., Daems, K., & Van de Velde, L. J. (2022). Growers' adoption intention of innovations is crucial to establish a sustainable greenhouse horticultural industry: An empirical study in Flanders and the Netherlands. *Journal of Cleaner Production*, *330*, 129752. https://doi.org/10.1016/j.jclepro.2021.129752

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information*

Systems Research, *2*(3), 192–222. https://doi.org/10.1287/isre.2.3.192
Morris, M. G., & Venkatesh, V. (2000). Age differences in technology adoption decisions: Implications for a changing work force. *Personnel Psychology*, *53*(2), 375–403. https://doi.org/10.1111/j.1744-6570.2000.tb00206.x
Mulinde, C., Majaliwa, J. G. M., Twinomuhangi, R., Mfitumukiza, D., Komutunga, E., Ampaire, E., Asiimwe, J., Van Asten, P., & Jassogne, L. (2021). Perceived climate risks and adaptation drivers in diverse coffee landscapes of Uganda. *NJAS: Wageningen Journal of Life Sciences*, *88*(1), 31–44. https://doi.org/10.1016/j.njas.2018.12.002
Nakabugo, R., Mukwaya, I. P., & Geoffrey, S. (2019). Adoption of climate smart agricultural technologies and practices in drylands in uganda: Evidence from a microlevel study in Nakasongola district. *Agriculture and Ecosystem Resilience in Sub Saharan Africa: Livelihood Pathways Under Changing Climate*, *30*(3), 541–568. https://doi.org/10.1007/978-3-030-12974-3_24
Ndamani, F., & Watanabe, T. (2016). Determinants of farmers' adaptation to climate change: A micro level analysis in Ghana. *Scientia Agricola*, *73*(3), 201–208. https://doi.org/10.1590/0103-9016-2015-0163
Ngeywo, J., Basweti, E., & Shitandi, A. (2015). Influence of Gender, Age, marital status and farm size on coffee production: A case of Kisii County, Kenya. *Asian Journal of Agricultural Extension, Economics & Sociology*, *5*(3), 117–125. https://doi.org/10.9734/ajaees/2015/15702
Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd. ed.). McGraw-Hill, Inc.
Nyasimi, M., Kimeli, P., Sayula, G., Radeny, M., Kinyangi, J., & Mungai, C. (2017). Adoption and dissemination Pathways for climate-smart Agriculture technologies and practices for climate-resilient livelihoods in Lushoto, Northeast Tanzania. *Climate*, *5*(3), 63. https://doi.org/10.3390/cli5030063
Oberski, D. (2014). Lavaan. survey: An R package for complex survey analysis of structural equation models. *Journal of Statistical Software*, *57*(1), 1–27. https://doi.org/10.18637/jss.v057.i01
Ogola, R. J. O., Ouko, K. O., & Tejada Moral, M. (2021). Synergies and trade-offs of selected climate smart agriculture practices in Irish potato farming, Kenya. *Cogent Food & Agriculture*, *7*(1), 1948257. https://doi.org/10.1080/23311932.2021.1948257
Oliveira, T., & Martins, M. F. (2011). Literature review of information technology adoption models at firm level. *The Electronic Journal of Information Systems Evaluation*, *14*(1), 110-121–pp110-121.
Oliveira, J. R. D., Santana, W. D. R., Altoé, J. A., Carrion, P. A. N., Baldan, W. G., Lima, A. S., Rosa, L. V. C. A. F., Gomes, R. D. S., Cavalcanti, A. C., Nascimento, A. D. L., & Oliveira, V. D. S. (2021). Integrated Pest Management In Coffee. *International Journal of Plant & Soil Science*, *2021*, 9–16. https://doi.org/10.9734/ijpss/2021/v33i1430496
Opio, E. (2019). *Influence of climate change on household food security in Uganda: A case study of Luweero district*. Nkumba University.
Oseni, T. O., & Masarirambi, M. T. (2011). Effect of climate change on maize (zea mays) production and food security in Swaziland. *American-Eurasian Journal of Agricultural Environment Science*, *11*(3), 385–391.
Pagliacci, F., Defrancesco, E., Mozzato, D., Bortolini, L., Pezzuolo, A., Pirotti, F., Pisani, E., & Gatto, P. (2020). Drivers of farmers' adoption and continuation of climate-smart agricultural practices. A study from northeastern Italy. *Science of the Total Environment*, *710*, 136345. https://doi.org/10.1016/j.scitotenv.2019.136345
Palombi, L., & Sessa, R. (2013). Climate-Smart Agriculture. In *Climate-Smart Agriculture Sourcebook* (2nd ed., Vol. 9, pp. 1–56). Food and Agriculture Organization of the United Nations (FAO). https://www.fao.org/docrep/018/i3325e/i3325e.pdf
Parveen, F., Jaafar, N. I., & Ainin, S. (2016). Social media's impact on organizational performance and entrepreneurial orientation in organizations. *Management Decision*, *54*(9), 2208–2234. https://doi.org/10.1108/MD-08-2015-0336
Passarelli, M., Bongiorno, G., & Cariola, A. (2021). Technology adoption in agriculture: a new entrepreneurial approach is possible? *Agribusiness and Information Management*, *13*(1), 1–25.
Pathak, H. S., Brown, P., & Best, T. (2019). A systematic literature review of the factors affecting the precision agriculture adoption process. *Precision Agriculture*, *20*(6), 1292–1316. https://doi.org/10.1007/s11119-019-09653-x
Pickens, J. (2005). Attitudes and perceptions. *Organizational Behavior in Health Care*, 4(7), 43–76.
Pindado Tapia, E., & Sánchez García, M. (2017). Researching the entrepreneurial behaviour of new and existing ventures in European agriculture. *Small Business Economics*, *49*(2), 421–444. https://doi.org/10.1007/s11187-017-9837-y
Ping, R. A. (2004). On assuring valid measures for theoretical models using survey data. *Journal of Business Research*, *57*(2), 125–141. https://doi.org/10.1016/S0148-2963(01)00297-1
Rahn, E., Läderach, P., Baca, M., Cressy, C., Schroth, G., Malin, D., van Rikxoort, H., & Shriver, J. (2014). Climate change adaptation, mitigation and livelihood benefits in coffee production: Where are the synergies? *Mitigation and Adaptation Strategies for Global Change*, *19*(8), 1119–1137. https://doi.org/10.1007/s11027-013-9467-x
Rajendran, N., Tey, Y. S., Brindal, M., Ahmad Sidique, S. F., Shamsudin, M. N., Radam, A., & 1Abdul Hadi, A. H. I. (2016). Factors influencing the adoption of bundled sustainable agricultural practices: A systematic literature review. *International Food Research Journal*, *23*(5), 2271–2279. https://web.s.ebscohost.com/abstract?direct=true&profile=ehost&scope=site&authtype=crawler&jrnl=19854668&AN=119017236&h=g52%2b0ZDXSvM7rGnqZmzNyRt1EoZ2SivaIsBL5hqF6%2f8Yi9jR5q3VQQ9LgNYCx202CC0zhP%2b5AU3QUF0qGtvK6Q%3d%3d&crl=c&resultNs=AdminWebAuth&resultLocal=ErrCrlNotAuth&crlhashurl=login.aspx%3fdirect%3dtrue%26profile%3dehost%26scope%3dsite%26authtype%3dcrawler%26jrnl%3d19854668%26AN%3d119017236
Ramos de Luna, I., Montoro-Ríos, F., & Liébana-Cabanillas, F. (2016). Determinants of the intention to use NFC technology as a payment system: An acceptance model approach. *Information Systems & E-Business Management*, *14*, 293–314. https://doi.org/10.1007/s10257-015-0284-5
Rogers, E. (1995). *Diffusion of innovations* (Fourth Paperback ed.).
Rogers, E. (2003). *Rogers' diffusion of innovations theory*.
Samaradiwakara, G., & Gunawardena, C. (2014). Comparison of existing technology acceptance theories and models to suggest a well improved theory/model. *International Technical Sciences Journal*, *1*(1), 21–36.
Sangroya, D., & Nayak, J. K. (2017). Factors influencing buying behaviour of green energy consumer. *Journal*

of Cleaner Production, *151*, 393–405. https://doi.org/10.1016/j.jclepro.2017.03.010

Sardar, A., Kiani, A. K., & Kuslu, Y. (2021). Does adoption of climate-smart agriculture (CSA) practices improve farmers' crop income? Assessing the determinants and its impacts in Punjab province, Pakistan. *Environment Development and Sustainability*, *23*(7), 10119–10140. https://doi.org/10.1007/s10668-020-01049-6

Schepers, J., & Wetzels, M. (2007). A meta-analysis of the technology acceptance model: Investigating subjective norm and moderation effects. *Information & Management*, *44*(1), 90–103. https://doi.org/10.1016/j.im.2006.10.007

Sebatta, C., Mugisha, J., Bagamba, F., Nuppenau, E. A., Domptail, S. E., Kowalski, B., Hoeher, M., Ijala, A. R., Karungi, J., & Tejada Moral, M. (2019). Pathways to sustainable intensification of the coffee-banana agroecosystems in the mt. Elgon region. *Cogent Food & Agriculture*, *5*(1), 1611051. https://doi.org/10.1080/23311932.2019.1611051

Sekabira, H., Tepa-Yotto, G. T., Djouaka, R., Clottey, V., Gaitu, C., Tamò, M., Kaweesa, Y., & Ddungu, S. P. (2022). Determinants for deployment of climate-smart integrated pest management practices: A meta-analysis approach. *Agriculture*, *12*(7), 1052. https://doi.org/10.3390/agriculture12071052

Senyolo, M. P., Long, T. B., Blok, V., & Omta, O. (2018). How the characteristics of innovations impact their adoption: An exploration of climate-smart agricultural innovations in South Africa. *Journal of Cleaner Production*, *172*(172), 3825–3840. https://doi.org/10.1016/j.jclepro.2017.06.019

Senyolo, M. P., Long, T. B., Blok, V., Omta, O., & van der Velde, G. (2021). Smallholder adoption of technology: Evidence from the context of climate smart agriculture in South Africa. *Journal of Development and Agricultural Economics*, *13*(2), 156–173. https://doi.org/10.5897/JDAE2020.1191

Serote, B., Mokgehle, S., Du Plooy, C., Mpandeli, S., Nhamo, L., & Senyolo, G. (2021). Factors influencing the adoption of climate-smart irrigation technologies for sustainable crop productivity by smallholder farmers in arid areas of South Africa. *Agriculture*, *11*(12), 1222. https://doi.org/10.3390/agriculture11121222

Shaw, H., Ellis, D. A., & Ziegler, F. V. (2018). The technology integration model (TIM). Predicting the continued use of technology. *Computers in Human Behavior*, *83*, 204–214. https://doi.org/10.1016/j.chb.2018.02.001

Shekmohammed, S., Mahmud, F., Asaduzzaman, M., Hany, U., Mahbub, M. (2022). The role of agroforestry in ecosystem maintenance and climate change Regulation: A Review.

Son, J.-Y., & Benbasat, I. (2007). Organizational buyers' adoption and use of B2B electronic marketplaces: Efficiency-and legitimacy-oriented perspectives. *Journal of Management Information Systems*, *24*(1), 55–99. https://doi.org/10.2753/MIS0742-1222240102

Sun, S., Yang, X., Lin, X., Sassenrath, G. F., & Li, K. (2018). Climate-smart management can further improve winter wheat yield in China. *Agricultural Systems*, *162*, 10–18. https://doi.org/10.1016/j.agsy.2018.01.010

Suvanto, H., Niemi, J. K., & Lähdesmäki, M. (2020). Entrepreneurial identity and farmers' protein crop cultivation choices. *Journal of Rural Studies*, *75*, 174–184. https://doi.org/10.1016/j.jrurstud.2020.01.022

Tageo, V., CBMS, D., Chronaki, C., Lowe, C., Berler, A., & Porcu, F. (2020). Business model canvas for adoption of International patient summary standards in mHealth industry. *Journal of Business Models*, *8*(3), 91–106.

Taherdoost, H. (2018). Taherdoost H: A review of technology acceptance and adoption models and theories. *Procedia Manufacturing*, *22*, 960–967. https://doi.org/10.1016/j.promfg.2018.03.137

Tama, R. A. Z., Hoque, M. M., Liu, Y., Alam, M. J., & Yu, M. (2023). An application of partial least squares structural equation modeling (PLS-SEM) to examining farmers' behavioral attitude and intention towards conservation Agriculture in Bangladesh. *Agriculture*, *13*(2), 503. https://doi.org/10.3390/agriculture13020503

Taylor, M. (2018). Climate-smart agriculture: What is it good for? *The Journal of Peasant Studies*, *45*(1), 89–107. https://doi.org/10.1080/03066150.2017.1312355

Teklewold, H., Kassie, M., & Shiferaw, B. (2013). Adoption of Multiple Sustainable Agricultural Practices in Rural Ethiopia. *Journal of Agricultural Economics*, *64*(3), 597–623. https://doi.org/10.1111/1477-9552.12011

Tesfaye, K. Kassie, M. Cairns, J. E. Michael, M. Stirling, C. Tsedeke Abate, B. M. P. Mekuria, M. Hailu, H. Bahadur Rahut, D. Erenstein, O. & Gerard, B. (2017). Potential for scaling up climate smart agricultural practices: examples from sub-Saharan Africa. *Climate Change Adaptation in Africa: Fostering Resilience and Capacity to Adapt*, 4(2), 185–203. https://doi.org/10.1007/978-3-319-49520-0_12

Tran, H., Simelton E., & Quinn C. (2017). *CGSpace*. 124. CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS). https://cgspace.cgiar.org/handle/10568/80703

Tripathi, A., Tripathi, D. K., Chauhan, D. K., Kumar, N., & Singh, G. S. (2016). Paradigms of climate change impacts on some major food sources of the world: A review on current knowledge and future prospects. *Agriculture, Ecosystems & Environment*, *216*, 356–373. https://doi.org/10.1016/j.agee.2015.09.034

Tsai, T.-H., Chang, H.-T., Ho, Y.-L., & Federici, S. (2016). Perceptions of a specific family communication application among grandparents and grandchildren: An extension of the technology acceptance model. *PloS One*, *11*(6), e0156680. https://doi.org/10.1371/journal.pone.0156680

UBOS. (2018a). The 2018 Statistical report. https://www.ubos.org/wp-content/uploads/publications/05_2019STATISTICAL_ABSTRACT_2018.pdf

UBOS. (2019). The 2019 Statistical report

UBOS. (2018b). The 2018 Statistical report . Uganda Bureau of Statistics, 345.

UCC. (2011). District information portal, Luwero district.

UCDA. (2015). Uganda national coffee strategy 2040 plan for 2015/16-2019/20. https://ugandacoffee.go.ug/index.php/file-download/download/public/35.

UCDA. (2019a). Robust Coffee Handbook. https://greeninguganda.com/images/product/coffee/robusta.pdf/

UCDA. (2019b). Robust coffee handbook. https://greeninguganda.com/images/product/coffee/robusta.pdf

Van Kleef, G. A., Gelfand, M. J., & Jetten, J. (2019). The dynamic nature of social norms: New perspectives on norm development, impact, violation, and enforcement. *Journal of Experimental Social Psychology*, *84*, 103814. https://doi.org/10.1016/j.jesp.2019.05.002

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540

Venkatesh, V., & Thong, J. Y. (2012). Xu X: Consumer acceptance and use of information technology:

Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157–178. https://doi.org/10.2307/41410412

Venkateswarlu, B. (2017). Climate Change and Climate Variability. In Valavida, V., & Karaba, N. (Eds.), *Agriculture Under Climate Change: Threats, Strategies and Policies* (Vol. *1*, p. 22).

Victory, G. O., Oyewole, A. L., & Olaitan, A. A. (2022). Climate-smart agricultural practices at Oyo State-Nigeria. *South Asian Journal of Social Review (ISSN: 2958-2490)*, *1*(1), 1–7. https://doi.org/10.57044/SAJSR.2022.1.1.2201

Vincent, A., & Balasubramani, N. (2021). Climate-smart agriculture (CSA) and extension advisory service (EAS) stakeholders' prioritisation: a case study of Anantapur district, Andhra Pradesh, India. *Journal of Water and Climate Change*, *12*(8), 3915–3931. https://doi.org/10.2166/wcc.2021.329

Vondolia, G. K., Eggert, H., & Stage, J. (2021). The effect of fertilizer subsidies on investment in soil and water conservation and productivity among Ghanaian farmers using mechanized irrigation. *Sustainability*, *13*(15), 8242. https://doi.org/10.3390/su13158242

Waaswa, A., Oywaya Nkurumwa, A., Mwangi Kibe, A., & Ngeno Kipkemoi, J. (2022). Climate-Smart agriculture and potato production in Kenya: Review of the determinants of practice. *Climate and Development*, *14*(1), 75–90. https://doi.org/10.1080/17565529.2021.1885336

Wang, O., De Steur, H., Gellynck, X., & Verbeke, W. (2015a). Motives for consumer choice of traditional food and European food in mainland China. *Appetite*, *87*, 143–151. https://doi.org/10.1016/j.appet.2014.12.211

Wang, O., De Steur, H., Gellynck, X., & Verbeke, W. (2015b). Motives for consumer choice of traditional food and European food in mainland China. *Appetite*, *87*(87), 143–151. https://doi.org/10.1016/j.appet.2014.12.211

Wesana, J., De Steur, H., Dora, M. K., Mutenyo, E., Muyama, L., & Gellynck, X. (2018). Towards nutrition sensitive agriculture. Actor readiness to reduce food and nutrient losses or wastes along the dairy value chain in Uganda. *Journal of Cleaner Production*, *182* (182), 46–56. https://doi.org/10.1016/j.jclepro.2018.02.021

Wiredu, A. N., Zeller, M., Diagne, A., Diagne, A., & Dogbe, W. (2015). Aliou: What determines adoption of fertilizers among rice-producing households in Northern Ghana? *Journal of Sustainable Development*, *7*(1). https://doi.org/10.5539/jsd.v7n1p167

Workman, M. (2014). New media and the changing face of information technology use: The importance of task pursuit, social influence, and experience. *Computers in Human Behavior*, *31*, 111–117. https://doi.org/10.1016/j.chb.2013.10.008

Wu, B., & Chen, X. (2017). Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model. *Computers in human behavior. Computers in Human Behavior*, *67*, 221–232. https://doi.org/10.1016/j.chb.2016.10.028

Yang, S., Lu, Y., Gupta, S., Cao, Y., & Zhang, R. (2012). Mobile payment services adoption across time: An empirical study of the effects of behavioral beliefs, social influences, and personal traits. *Computers in Human Behavior*, *28*(1), 129–142. https://doi.org/10.1016/j.chb.2011.08.019

Zahra, S. A. (2018). Entrepreneurial risk taking in family firms: The wellspring of the regenerative capability. *Family Business Review*, *31*(2), 216–226. https://doi.org/10.1177/0894486518776871

Zerssa, G., Feyssa, D., Kim, D.-G., & Eichler-Löbermann, B. (2021). Challenges of smallholder farming in Ethiopia and opportunities by adopting climate-smart agriculture. *Agriculture*, *11*(3), 192. https://doi.org/10.3390/agriculture11030192

Zeweld, W., Van Huylenbroeck, G., Tesfay, G., & Speelman, S. (2017). Smallholder farmers' behavioural intentions towards sustainable agricultural practices. *Journal of Environmental Management*, *187*, 71–81. https://doi.org/10.1016/j.jenvman.2016.11.014