# EFFECT OF BLOCKCHAIN TECHNOLOGY ON THE PERFORMANCE OF BARLEY FARMERS IN EASTERN UGANDA

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**A Thesis Submitted to the Graduate School in Partial Fulfilment of the Requirements for the Doctor of Philosophy Degree in Agribusiness Management of Egerton University**

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## DECLARATION AND RECOMMENDATION

### Declaration

This thesis is my original work and has not been presented in this University or any other for the award of a degree

Signature: Date: 30th September, 2025

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### Recommendation

This research proposal has been submitted with our approval as university supervisors

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## DEDICATION

I dedicate this thesis to my family for their immense support.

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## ABSTRACT

Barley has the potential to significantly boost smallholder farmers' gross margins in Uganda due to its diverse applications in animal feed, bakeries, and pharmaceuticals, with the highest demand from the local brewing industry. However, productivity remains low due to poor-quality output, limited access to inputs, and a lack of transparency and trust in the value chain. To address these challenges, the Ugandan government and barley value chain stakeholders introduced BanQu (Bank You) blockchain technology. Despite this, adoption remains low, and value chain challenges persist. Limited research exists on blockchain adoption barriers, its effect on barley productivity and gross margin, and its effectiveness in addressing value chain challenges. This study addressed the gap by 1) determining farmers' behavioural intentions to adopt blockchain; 2) examining the factors influencing adoption and usage extent; 3) determining blockchain's effect on productivity and gross margins; and 4) developing a suitable implementation framework for Uganda. A mixed-methods explanatory sequential design was used, involving a survey of 491 barley farmers, 2 group discussions, and 8 key informant interviews. Data were analysed using SMART PLS (objective 1), STATA (objectives 2 and 3), and XLSTAT (objective 4). Findings showed that the technology acceptance model and social norm analysis sufficiently predicted farmers' behavioural intentions at 49.9% and 42.5%, respectively. Key factors positively influencing blockchain adoption included frequency of blockchain training, network stability, production costs, land size, compatibility, and phone ownership, while marital status, training costs, land tenure, distance to buying centres, initial cost of blockchain, and marketing costs hindered adoption. Extent of blockchain use was higher among farmers with greater training frequency, lower training costs, higher education, and group membership but lower among those with larger land sizes, higher initial costs, and greater distances to buying centres. Blockchain adoption increased barley productivity and gross margins by 0.91 and 0.93 units, respectively. The priority challenges to implementation were farmer-related, followed by those linked to the barley buying company, middlemen, regulatory issues, and technology-related challenges. A fishbone diagram framework was developed to guide in addressing these challenges. The study recommended collaboration between the government, the barley buying Company, and other stakeholders to train farmers and middlemen on blockchain benefits, and a cost-sharing approach to lower blockchain implementation costs. Adoption of the proposed framework was advised to streamline blockchain technology implementation and maximize its potential benefits.

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| | |
|---|---|
| **AHP** | Analytic Hierarchy Process |
| **ATT** | Average Treatment Effect on the Treated |
| **ATU** | Average Treatment Effect on the Untreated |
| **BCT** | Blockchain technology |
| **CI** | Consistency Index |
| **CR** | Consistency Ratio |
| **DEMATEL** | Decision Making Trial and Evaluation Laboratory |
| **DHM** | Double Hurdle Model |
| **ESR** | Endogenous Switching Regression |
| **FIML** | Full Information Maximum Likelihood |
| **ICTs** | Information and Communication Technologies |
| **KIs** | Key Informants |
| **KIIs** | Key Informant Interviews |
| **MCDM** | Multi-Criteria Decision Making |
| **MoU** | Memorandum of Understanding |
| **PEAP** | Poverty Eradication Action Plan |
| **PEU** | Perceived Ease of Use |
| **PLS-SEM** | Partial Least Squares Structural Equation Modelling |
| **PPS** | Probability Proportional to Size |
| **PSM** | Propensity Score Matching |
| **PU** | Perceived Usefulness |
| **RI** | Random Index |
| **SAOs** | Sub-County Officers |
| **SDGs** | Sustainable Development Goals |
| **SMS** | Short Message Service |
| **SSA** | Sub-Saharan Africa |
| **SWOT** | Strengths Weaknesses Opportunities and Threats |
| **TAM** | Technology Acceptance Model |
| **TFP** | Total Factor Productivity |

| | |
|---|---|
| **TPB** | Theory Planned Behaviour |
| **UBOS** | Uganda Bureau of Statistics |
| **UNHS** | Uganda National Household Survey |
| **USD** | United States Dollars |
| **USAID** | United States Agency for International Development |
| **UT** | Utility Theory |
| **UTAUT** | Unified Theory of Acceptance and Utilization of Technology |

# CHAPTER ONE

# INTRODUCTION

## 1.1 Background of the study

Agriculture remains the backbone of most economies worldwide, especially in Sub-Saharan Africa (SSA) (World Bank, 2018). In this region, smallholder farmers are essential in the effort of achieving the Sustainable Development Goal (SDGs) of eradicating hunger and poverty (Terlau *et al*., 2019). Despite this, the performance of smallholder farms is still low. Against this backdrop, there is an increasing need to improve the efficiency of smallholder farms if agriculture is to serve its role as an engine for SSA economic growth. Technology could play a substantial part in enabling agriculture achieve its role, but the adoption of agricultural technologies in many agrifood farming systems, including barley value chains still lags behind (Kittipanya-ngam & Tan, 2020).

Barley is a global crop produced by more than 100 countries and is the fourth most important grain crop in the world after wheat, maize and rice. Europe is the leading producer of barley, accounting for over 60% of global output, followed by Asia with 15% and America with 13% (Giraldo *et al*., 2019). In Africa, barley is mostly grown in the top six nations namely Morocco, Ethiopia, South Africa, Kenya, Egypt, and Algeria (Wada *et al*. 2022).

Barley is an emerging crop in Uganda with the potential of increasing smallholder farmers' incomes (Rashid *et al*., 2019). This is because of its readily available market both locally and overseas, and its diverse uses. Barley is a source of food for humans and feed to livestock (Punia, 2020). It is a raw material for the bakery industry and is a source of functional ingredients for the treatment of chronic diseases like diabetes, cancer, mental illness, and cardiac diseases (Zeng *et al*., 2020). However, its primary use is in the brewing industry (Ganewo *et al*., 2022).

Currently, the local annual demand for barley in Uganda is very high and unsatisfied. This demand was recently reported at 100,000metric tonnes per annum. Barley is grown in almost all the four regions of Uganda, but eastern Uganda is the leading producer, particularly in Sebei sub-region (Kapchorwa, Bukwo and Kween) (Kagorora *et al*., 2021). Kapchorwa alone produces about 5,000 metric tonnes equivalent to (5%) of the annual local demand, while the rest of the production is largely not documented. The main buyers are the brewing companies (PanAfrican Agriculture, 2023), with Company B (not real name for purposes of anonymity), buying over 90% of the barley produced locally, followed by Uganda Breweries Limited as the major competitor. Despite eastern

Uganda being the lead producer, barley productivity in the region remains low unable to meet local demand. This is exacerbated by the high levels of poverty in this region, having ranked one of the poorest in Uganda (Uganda Bureau of Statistics [UBOS], 2020) for almost a decade.

In order to increase barley production, the government of Uganda reduced the excise tax on beer brewed with locally grown barley to 40% since 2009, and since 2017, the excise duty has been at 30% (Ugx 950 per litre/USD 0.26) (Kavuma *et al*., 2020). Other initiatives aimed at increasing barley production include initiatives by brewing companies, the Government's Poverty Eradication Action Plan (PEAP), and the USAID-funded Agricultural Productivity Improvement Program (APEP). These initiatives have provided support to barley farmers (Kagorora *et al*., 2021). Despite these efforts, barley farms still face a myriad of challenges in input sourcing, output supply, fluctuating prices, exploitation by middlemen, continued outsourcing of barley from neighbouring countries, and poor-quality barley which is often rejected at Company B. In 2019, a concerted effort from the stakeholders in the barley value chain, and Ugandan government, to solve these challenges and increase productivity led to the introduction of BanQu ("Bank You") blockchain technology (BCT). However, limited empirical studies have been carried out in regards to how blockchain technology has progressed in tackling the barley value chain challenges.

Blockchain technology is a decentralized, secure digital ledger that facilitates data transmission and storage, improving transparency, traceability, and trust across the users (Park & Li, 2021). In the Ugandan context, a blockchain based technology known as BanQu is used in the barley value chain activities. The activities include input sourcing, production and output supply to Company B. BanQu operates by having smallholder farmers connect their phones to the BanQu blockchain software app and allows them to register and store their value chain activities data, and receive short message services (SMSs) upon each transaction. The SMSs received contain immutable information on prices to be offered to farmers at the end of each season, prices of inputs (such as seeds, fertilizers, packing materials, and transportation costs to Company B buying centres), Company B field staff extension days as per farmers' location, payment details after supply, among others.

Moreover, BanQu blockchain technology enables farmers who lack the funds to purchase inputs such as seeds, fertilizers at the start of the season to obtain these inputs and pay for them when they deliver the produce to Company B buying centres. When Company B is paying farmers, blockchain technology gives the farmer the option of receiving cash, mobile money deposit, or bank account deposits, all of which have globally accessible, immutable records (Kumarathunga *et al*., 2022). These records can at any time be printed out and presented to financial institutions as security for credit or to governmental agencies in search of financial support in form of grants (Tripoli & Schmidhuber, 2020). The adopters of blockchain technology alone are entitled to these benefits. Eventually, blockchain technology reduces transaction costs associated with barley production and supply activities for the adopters (Bhusal, 2021). The non-adopters, on the other hand, rely solely on their ability to bargain with middlemen, and other input suppliers who often take advantage of them. Access to inputs by non-adopters is impossible without cash payments, which predisposes farmers to use of low-grade inputs that lower the quality of their output, leading to frequent rejections at Company B buying centres.

This way, blockchain technology innovation guarantees that every farmer (adopters), regardless of their financial status, is globally visible along the barley value chain, their economic identity secured, and their transaction history recorded (Kshetri, 2021). However, since BanQu blockchain technology's introduction in 2019, only one out of the four regions in Uganda (eastern) have adopted it, and its future use is uncertain. Even in this region, not all farmers produce and supply barley through BanQu BCT platform, unknown yet are the factors that have led to this pattern. Unlike in Zambia, where there are evidences of BanQu blockchain technology improving the performance of the cassava farms (Agarwal, 2022; Lee *et al*., 2022), such evidences are unavailable in the Ugandan barley value chain context. This research seeks to address this information gap by determining farmers' acceptance and adoption of blockchain technology, blockchain technology's effect on barley farms' performance, and finding out the critical challenges impeding blockchain scalability in order to come up with a suitable implementation framework for successful blockchain implementation in Uganda.

**1.2 Statement of the problem**

Despite the potential of blockchain technology to enhance barley farming in eastern Uganda, farmers continue to struggle with low productivity and profitability. Barley yields remain suboptimal, and the returns farmers receive from selling their produce are inadequate. However, farmers face challenges such as price volatility, limited market access, lack of transparency, and weak traceability in the value chain. While blockchain technology offers a potential solution, its actual impact on farm productivity and farmers' gross margins remains unclear. Additionally, the reasons for the uneven adoption of blockchain technology among barley farmers and across different regions are not well understood. Persistent inefficiencies in the barley value chain contribute to low productivity and profitability. These include poor-quality barley produce, limited access to inputs, farmer exploitation by middlemen, and the importation of barley from neighbouring countries, which is then passed off as Ugandan due to its competitive advantages in quality and quantity. It remains uncertain how BanQu blockchain technology is addressing these challenges to enhance the performance of barley farms. Previous studies on blockchain technology in agriculture have primarily focused on its effects on the supply chain performance of large agribusiness firms, particularly in terms of transparency, traceability, product quality, and responsiveness. However, there is limited empirical evidence on how blockchain technology effects smallholder farmers' productivity and gross margin, especially in the context of eastern Uganda's barley value chain. This study seeks to bridge this gap by examining farmers' acceptance and adoption of BanQu blockchain technology, and evaluating its effect on productivity and gross margin of barley farmers in eastern Uganda. Additionally, the study identifies key challenges associated with blockchain implementation, prioritizes them, and proposes solutions to develop a suitable implementation framework for Uganda's barley sector.

## 1.3 Objectives

### 1.3.1 General objective

To enhance the productivity and profitability of Ugandan smallholder barley farmers through the use of blockchain technology for improved livelihoods.

### 1.3.2 Specific objectives

i) To determine farmers' behavioural intention to accept blockchain technology in Uganda's eastern barley producing region.

ii) To determine the factors that influence adoption and extent of use of blockchain technology among barley farmers in eastern Uganda.

iii) To determine the effect of blockchain technology on barley farmers' productivity and gross margin in eastern Uganda

iv) To develop suitable blockchain technology implementation framework among barley farmers in eastern Uganda.

## 1.4 Research questions

i) What determines farmers' behavioural intention to accept blockchain technology in Uganda's eastern barley producing region?

ii) What factors influence adoption and extent of use of blockchain technology among barley farmers in eastern Uganda?

iii) What is the effect of blockchain technology on the productivity and gross margin of barley farms in eastern Uganda?

iv) What is the suitable blockchain technology implementation framework among barley farmers in eastern Uganda?

**1.5 Justification of the study**

Barley production is a growing agricultural enterprise in Uganda with the potential to transform smallholder farmers' livelihoods. In the current Fourth Industrial Revolution (4.0), stakeholders such as policymakers under the Uganda National Agricultural Policy view the integration of cost-effective, cutting-edge technologies in barley farming as a means to enhance productivity and increase farmers' gross margins. To support this vision, in 2019, the Ugandan government, through the Ministry of Agriculture, Animal Industry, and Fisheries (MAAIF), along with the main barley buyer, Company B, committed to promoting the use of local materials in supplying breweries. As part of this commitment, Company B pledged to prioritize purchasing all barley from Ugandan farmers before resorting to imports. To uphold this commitment, BanQu blockchain technology was introduced to uniquely identify local barley supplies, distinguish them from imports, eliminate farmer exploitation by middlemen, improve trust, and improve transparency through addressing price information asymmetry. The assured market for farmers and reliable supply for Company B was expected to enhance barley farm productivity and farmers' gross margins. The findings of this study will help stakeholders in the barley value chain evaluate the progress of blockchain technology in achieving these objectives.

The study findings are important because the current Uganda National household survey (UNHS) statistics ranked eastern region as the second poorest region (UBOS, 2020). Therefore, interventions by Uganda's Poverty Eradication Action Plan (PEAP), and those highlighted in the Poverty Reduction Strategy Paper may be interested in this study findings. Also, the findings may guide in achieving the SDGs 1 (zero poverty) and 2 (zero hunger). The study findings further provide reference points regarding BCT scalability.

**1.6 Scope and limitations of the study**

The study was carried out in eastern Uganda, specifically in the districts of Bukwo and Kween. Focus was on the three actors in the barley value chain namely smallholder farmers, middlemen, and Company B staff. Farmers using blockchain and those not using it, were included to establish the differences and similarities, if any, in terms of blockchain technology acceptance, adoption, and productivity and gross margin. Semi-structured questionnaires, group discussions (GDs), and key informant interviews (KIIs) collected data from farmers and stakeholders in the barley value chain.

The limitations of the study were primarily related to its focus, data collection methods, and technological scope. This study was conducted among barley farmers in eastern Uganda, providing valuable insights specific to this population but limiting the broader applicability of the findings. Differences in agricultural practices, infrastructure, and socio-economic conditions across regions and countries may affect the generalizability of the results. Additionally, data collection relied on self-reported surveys, interviews, and group discussions, which, while offering direct insights, introduced potential response biases such as social desirability or recall bias, possibly leading to over- or underestimation of productivity, experiences, or perceptions of blockchain technology. Furthermore, the study’s focus on blockchain technology means its findings may not fully apply to other digital or agricultural technologies. Given the rapid pace of technological advancements, factors influencing adoption and user experience are likely to evolve, highlighting the need for ongoing longitudinal studies to capture these changes over time.

### 1.7 Operational definition of terms

**Barley farms:** These entailed commercial oriented smallholder farmers engaged in barley production for the sole purpose of supply to Company B.

**Blockchain technology (BCT):** It is a shared distributed ledger technology (DLT) that facilitates recording of transactions right from input acquisition to processing of payments to farmers via bank, mobile accounts, or cash payments. BanQ blockchain technology, a non-crypto currency platform, was the focus of this study.

**Blockchain technology acceptance:** This encompasses an understanding of how barley farmers come to acknowledge the usefulness of blockchain technology, and thus, decide on whether to use it or not. Acceptance is the first step in technology adoption, and it was be based on the theory of planned behaviour.

**Blockchain technology adoption:** The integration and application/implementation of blockchain technology into the value chain activities of the barley Agri-enterprise, as undertaken by the actors under study (farmers, middlemen, buying company).

**Farm performance:** This was based on the measurements of productivity and gross margin.

**Gross margin:** This was given by the difference between total revenue and the total variable costs incurred by the farmer during barley production and marketing up to supply to Company B.

**Productivity:** This was defined in terms of yield of barley per hectare of land under barley cultivation

**Smallholder farmer:** A smallholder farmer for this study is one with barley farm size less or equal to 5 hectares (12.36 acres). This was adopted from FAO's definition (FAO, 2017)

**Social norm:** This refers to the individual farmer's beliefs and/ attitudes regarding whether other people think he or she should accept blockchain technology or not (subjective norm), groups of people sharing the same feeling about blockchain technology acceptance (normative reference groups like Company B staff, local authorities, middlemen, fellow farmers), and whether accepting or not accepting blockchain technology may result in negative or positive reaction from others (behavioural sanctions).

# CHAPTER TWO

# LITERATURE REVIEW

This chapter reviews the literature on agribusiness models aimed at enhancing farm performance, with a focus on advanced technologies such as blockchain. It explores various applications of blockchain across different sectors, particularly in the agrifood industry, while identifying key research gaps within the Sub-Saharan context. The chapter also reviews literature on the determinants of smallholder farmers' intentions to adopt blockchain, the factors influencing their decision and extent of adoption, the effect of blockchain technology on farm productivity and gross margins, and the challenges hindering its implementation. Additionally, the chapter outlines the theoretical and conceptual frameworks underpinning this study, and presents the barley value chain map under study.

## 2.1 Agribusiness models that target improved performance of smallholder farmers

With the rising need to increase performance of small-scale agribusinesses, different agribusiness models have been employed and others suggested by stakeholders in different agrifood value chains (Kelly *et al*., 2015). The most commonly used ones are; contract farming which ensures that farmers have assurance of the market and stable prices upon entering into a contract with produce buyers who on the other hand have assurance of supply (Pera *et al*., 2019). Contract farming has progressively shaped various crop value chains' performance in the recent past with the most benefit being realized in boosting the incomes of smallholder farmers (De Brauw & Bulte, 2021; Makoye, 2019). Farmer organizations have also played a role in boosting productivity and gross margins of smallholder farmers (Bizikova *et al*., 2020). Farmer organizations are of different types including producer organizations, marketing organizations, and cooperatives societies. Their overall mandate is to enable streamlined and profitable agrifood value chain activities right from input sourcing to output supply (Abdul-Rahaman & Abdulai, 2020).

By the year 2050, the advancement of agricultural technologies aimed at enhancing the productivity of smallholder agribusinesses is anticipated to continue accelerating, particularly in developing nations (Khan *et al*., 2021). Technologies like smart contracts have enabled processing of transactions among the parties involved in the contract in an automated fashion which would otherwise require trust from the parties to meet the terms and conditions of the contract (Pranto *et al., 2021)*. Actors in value chains are able to carry out their tasks with confidence that they will receive rewards for their efforts. Smart contracts operate on blockchain technology which eliminates the need for intermediaries and time loss during execution of contracts (Aggarwal & Kumar, 2021).

Blockchain technology has seen progress in improving various crop value chains in different countries such as Zambia and Kenya (Kshetri, 2021; Nzau, 2023). BanQu software app also operates on blockchain technology, and is one of the upcoming strategies used to improve the performance of agrifood value chains. While most blockchain-based technologies have focused on larger firms, this study focuses on BanQu blockchain technology, which aims to help smallholder farmers, the last-mile downstream stakeholders, improve their performance and gain recognition in global crop value chains.

### 2.2 Overview of Blockchain technology and its application in the agrifood sector

As one of the mega trends in the agrifood sector, technological change is considered a crucial factor to address as global economies strive for sustainable development. According to Ferreira *et al*. (2019), applying innovative technologies to the agrifood sector has many advantages, including improving total factor productivity, which entails increasing crop and animal production without increasing inputs like land, labour, or capital. It also improves the efficiency of all agrifood processes, and creating new business models. Some of the applauded technologies include precision agriculture, big data, smart contracts, robotics, artificial intelligence/machine learning, biotechnology, Internet of Things (IoT), and most recently, blockchain technology (Stranieri *et al*., 2021). These technologies have made significant progress in addressing the transparency, traceability, sustainability, productivity, and profitability issues in agrifood value chains, though much evidence is in developed countries, with less developed countries making relatively little progress (Abban & Abebe, 2022).

Additionally, evidence of BCT applications in agrifood processes is available for big firms and organizations. These include Walmart networks operating in various countries, the Caribbean Agribusiness Development Company in Trinidad and Tobago, which utilizes blockchain in the vegetable supply chain, the International Centre for Tropical Agriculture, which employs blockchain technology in Uganda's coffee value chain, and Bioversity International, which applies blockchain in cocoa value chain (Ballantyne & Addison, 2020). Blockchain ensures trust among the actors in these large value chains who would otherwise be untrusted (Kamilaris *et al*., 2019). Essential big data relating to farmers, the crops grown, the environment, and safety are traceable and transparent to all the actors which further enhances trust in global crop value chains (Kos &

Kloppenburg, 2019). While shared data appears to increase value chain transparency, concerns about data security remain, particularly when actors are not properly educated about why their data is being captured (Jakku *et al*., 2019). Nonetheless, there is limited empirical evidence for BCT applications involving smallholder farmers' owned farm enterprises (Quayson *et al*., 2021), such as the case of barley smallholder farmers in eastern Uganda.

BanQu BCT has the potential of recording and immutably storing transactions of individuals, but mostly of the less privileged and last mile clients like smallholder farmers (World Economic Forum, 2021). This economic identity would later be used for financial inclusion, equity, trade partnerships and overall economic growth of these individuals (Soriano, 2017). This blockchain technology based BanQu software app has been applied in various firms in different departments to create digital identity for individuals considered invisible on global stages. For example, in Zambia, BanQu is used in the smallholder cassava farms' supply chain management (Lee *et al*., 2022), in the US, it is used to create trusted digital identity for homeless people in need of emergency health care services in Texas so as to build their resilience (Khurshid & Gadnis, 2019), while in refugee camps, it is used by humanitarian organizations in delivering services to the vulnerable communities.

Overall, recent literature has proven blockchain technology's usefulness in sectors like government, finance, banking, and in agribusinesses but mainly in developed supply chains (Garg *et al*., 2021; Laroiya *et al*., 2020; Rijanto, 2021; Rocha *et al*., 2021). While studies on barley farms have mostly focused on barley agronomy, malting properties, contract farming, and genotypic diversity, minimal attention has been directed towards the applicability of blockchain in the barley value chain. This study sought to contribute to bridging this knowledge gap by examining the performance of the barley farms while leveraging digitalized technologies like BanQu blockchain.

### 2.3 Farmers' behavioural intention and acceptance of blockchain technology

In agrifood supply systems, Kramer *et al*. (2021) applied the technology acceptance model in combination with exploratory interviews to study behavioural intentions of stakeholders in coffee supply chain towards adopting blockchain technology. In the findings, a normative stakeholder management framework was developed which proposed that stakeholders need to keep close ties with management of companies for BCT implementation to be successful. However, this finding is different from that of Nayal *et al*. (2021) whose findings instead portray a negative significant relationship between top management support and blockchain technology adoption.

Furthermore, the results of Kramer *et al*. (2021) revealed that the developed framework positively influences blockchain technology use behaviour as was stakeholders' attitudes and perceived behavioural control. Their study, just like most empirical studies, analysed primary data from supply chain stakeholders in blockchain technology implementing companies, but excluded the smallholder coffee farmers, a gap this study intended to bridge by including the smallholder barley farmers in the analysis.

While studying the acceptance of Digital TurKish Lira, a blockchain based technology used in the banking industry of Turkey, Toraman (2022) used the technology acceptance model. In his study, technology acceptance model and partial least squares structural equation modelling were used to model clients' acceptance and consequent adoption of the technology. The results indicated that client's attitude had a positive effect on intention to use Digital TurKish Lira blockchain technology, and perceived usefulness had a positive effect on attitude towards use. Additionally, though perceived ease of use did not have any effect on attitude towards use, it had a positive effect on perceived usefulness. Toraman added only risk and environmental concern as antecedents for perceived usefulness and ease of use regarding acceptance, which seem to be a few variables when adopting most technologies involving last mile participants. Therefore, this study incorporated other variables like social norms, farmers' image, and blockchain technology's relevance to better estimate blockchain technology acceptance among smallholder barley farmers.

Based on the theory of planned behaviour, Saurabh and Dey (2021) examined the acceptance of blockchain integrated information and communication technologies (ICTs) in the management of grape wine supply chain. Using rating-based conjoint analysis, the dual found that product price, trust, compliance, traceability, coordination, and behavioural control have a positive influence on supply chain actors' intention to use blockchain integrated ICTs. As highlighted by Xiong *et al*. (2020), a common gap in the reviewed literature is the exclusion of last-mile individuals, such as smallholder farmers, from the analysis, with empirical studies notably lacking in the context of Uganda's barley farms.

### 2.3.1 Antecedents of perceived usefulness and perceived ease of use in the second extension of technology extension model

Seminal work by Moore and Benbasat (1991) describes the variable "image" as the extent to which using an innovation is thought to improve one's standing within their society. In this case, the degree to which use of blockchain is perceived to enhance the status of the farmer in the society.

This has a bearing on perceived usefulness of blockchain which may culminate in its acceptance. Nonetheless, research activities on image have instead focused on the technology's image other than user image. For instance, Bashir *et al*. (2022) and Izuagbe *et al*. (2019) studied the relationship between image, subjective norm and perceived usefulness of different technologies by utilizing technology acceptance model. Bashir *et al*. (2022) studied the intention to use social media sites among business-to-business fashion brands in Pakistan and found that the image of a given social media site has a positive significant effect on the user's perceived usefulness of the social media site. Further, subjective norm was also found to have a positive significant effect on perceived usefulness of the social media sites.

On the other hand, Izuagbe *et al*. (2019) studied intention to use social media technologies in university libraries and the findings revealed that the image associated with the social media technology and subjective norm were the leading determinants of perceived usefulness of social media usage in libraries. Remarkably, there is limitation of literature regarding the relationship between user image (in this case, barley farmer's image) and perceived usefulness of a technology as determinants of intention to use technologies in the agrifood sector, a gap this study intended to fill by exploring whether perceived farmer image as a result of the technology has an effect on the relationship between perceived usefulness and blockchain technology use intention.

This study adopted Venkatesh and Davis's (2000) definition of the construct relevance in reviewing the literature on blockchain relevance to barley value chain. Accordingly, relevance describes the extent to which barley farmers perceive that blockchain technology applies to their barley value chain activities, from input sourcing to output delivery. Zarafshani *et al*. (2020) evaluated the acceptance of technology among secondary school agricultural teachers in Iran and found relevance to have a significant positive effect on perceived usefulness of technology. In some studies, such as Kemp *et al*. (2019), relevance has been referred to as job-fit. In their study, Kemp *et al.* (2019) defined job-fit as the ability of a technology to enhance the user's performance (attaining gains). It was found that while using the technology acceptance model to access factors affecting acceptance of educational technologies, job relevance has an effect on perceived usefulness. Existing studies on the antecedents of the extended Technology Acceptance Model, including relevance, have been applied across various sectors but remain largely unexplored in the agrifood sector, a gap this study seeks to fill.

Perceived usefulness (PU) refers to the extent users believe a technology enhances their performance (Davis, 1989). Perceived usefulness has been found to be affected by output quality in determining the user behavioural intention to accept technologies. The extent to which the user believes that the technology will improve the overall quality of output greatly affects how useful the technology is perceived to be. In four field studies conducted by Venkatesh and Davis (2000) using the second extension of the Technology Acceptance Model, output quality was proposed to directly influence perceived usefulness. Moreno *et al*. (2017) hypothesized output quality to have a direct positive effect on perceived usefulness of e-learning platforms among university students. Moreno *et al.* (2017) employed the second extension of technology acceptance model to explain university students' intentions to accept e-learning platforms and established that output quality did not have a direct positive relationship with perceived usefulness.

However, in the third extension of the technology acceptance model, Venkatesh and Davis (2000) proposed output quality to have a moderating effect between job relevance and perceived usefulness. When output quality is high, users are more likely to see the technology as directly supporting their job tasks, thus strengthening the effect of job relevance on perceived usefulness. Moreover, evaluating performance or gains as a result of a technology (job relevance) might be aided by the quality of the output (Zaineldeen *et al*., 2020). In keeping with the analogy, and need to apply technology acceptance model in Uganda's agrifood sector, this study explored the moderating role that perceived barley output quality could possibly have on the association between perceived usefulness and blockchain technology's relevance to the barley value chain.

Result demonstrability is another important antecedent to perceived usefulness since it describes the perception of the tangibility of the results of a given technology. In this study's context, result demonstrability embodied farmers' perception on the tangibility of the results of using blockchain technology in barley value chain activities and how easily this can be communicated to others. An investigation by Soodan *et al*. (2024) into farmers' use of agro-advisory mobile applications was conducted in which result demonstrability was among the antecedents incorporated in the extended technology acceptance model. In their findings, result demonstrability positively influenced perceived usefulness, which, in turn, influenced farmers' intention to use the mobile applications. Also, in evaluating the drivers to adoption of agricultural green production technologies in China, Dai and Cheng (2022) extended technology acceptance model to include result demonstrability among other factors in their analysis. The results indicated a positive and significant contribution of result demonstrability to perceived usefulness. The current study intended to incorporate result demonstrability in the application of extended technology acceptance model in Uganda's barley value chain and blockchain acceptance context.

Research by Park *et al.* (2022) incorporated voluntariness as a construct affecting acceptance behaviour of intelligence-based technologies in the health sector. The original proposition in the third extension of technology acceptance model is that voluntariness moderates the relationship between subjective norm and user acceptance behaviour. Park and his colleagues instead conceptualized voluntariness to have a direct effect on acceptance behaviour. In their findings effected using partial least squares structural equation modelling, the authors found voluntariness to highly and positively impact the acceptance behaviour of the respondents. In this study, voluntariness plays a vital role since the technology was not mandatory to the farmers, as such acceptance would be attributed to how useful the technology was perceived to be. Therefore, in addition to exploring the moderating role of voluntariness on the association between subjective norm and behavioural intention, this study also hypothesised voluntariness to have a direct effect of perceived usefulness of blockchain technology.

**2.3.2 The context of social norms analysis in agricultural technology adoption**

The effects of social norms in the adoption of agricultural technology, including blockchain, cannot be over-emphasized. Scholars like Yanovitzky and Rimal (2006) have described social norms as characteristics of both individuals, such as people's perceptions of what others in their social environment do or expect them to do, and social groups, which involve individuals' connections with other group members. Similarly, Chung and Rimal (2016) referred to social norms as social frames of reference and conceptualized individual perceptions as being anchored around frames of reference provided by others.

Social norms influence beliefs and attitudes toward the behaviours of individuals in a societal setting. When individuals observe or believe that their peers approve of a certain behaviour, they are more likely to adopt favourable attitudes toward it. This phenomenon is explained by subjective norms within the Theory of Planned Behaviour, which suggests that people form attitudes based on perceived social expectations (Ajzen, 1985). Social norms create pressure to conform. Individuals tend to align their attitudes with the norms of their social group to gain social acceptance and avoid sanctions, such as social disapproval or exclusion (Douglas *et al.*, 2024). This is particularly important in collectivist cultures or cohesive rural communities where conformity is highly valued, like the Sebei sub-region under study. The positive or negative attitudes developed by the individuals as a result of conformity or non-conformity to the social norms would then influence the behaviours of the individual (Albarracin & Johnson, 2019; Ajzen, 1996). This study, thus, conceptualized that social norms influence farmers' attitudes which in turn influence behaviour intention to accept blockchain technology.

Among smallholder farmers, social norms include the informal rules and principles that group members follow without legal enforcement. Smallholder farmers typically seek group acceptance and aim to avoid social criticism or sanctions from others (Abrahamse & Steg, 2013). Such being the case, social norms can impose both tangible and intangible pressure, encouraging individuals to align their behaviour with the group (Heinicke *et al*., 2022). Regarding the adoption of agricultural technology, social norms influence the behaviour and acceptance of technology among farmers. This entails whether farmers choose to accept or reject new technologies can be greatly influenced by these social norms. Social norms are further categorized into subjective norms, injunctive norms, descriptive norms, normative reference groups, and behavioural sanctions.

Subjective norm refers to an individual's perception of how others view a specific behaviour. It reflects a person's assessment of the social pressure to engage in or avoid the behaviour. This typically includes beliefs about what family, friends, and colleagues, think about the behaviour's outcome and how these views influence the person's behaviour or motivation to conform. Subjective norms significantly influence the intention to use new or adopt agricultural technologies, including blockchain (Massoro & Adewale, 2019). According to Ajzen (1991), people may be encouraged or discouraged from embracing new behaviours (including technologies) depending on subjective norms. While studying the intention of farmers to adopt ecological agricultural technologies in China, Dong *et al*. (2022) used technology acceptance model effected through partial least squares structural equation modelling and established that subjective norm had a positive significant effect on intentions to adopt. Regarding blockchain and the barley value chain, an individual farmer's perception of other people's opinions such as family and friends, among others may influence the intention to accept blockchain technology.

Injunctive norms refer to the behavioural standards that most people either endorse or oppose and believe should or should not be followed. Injunctive norms include beliefs about what others think should be done, thus, the perceptions about what behaviours are socially approved or disapproved by others, essentially indicating what people ought to do based on moral or ethical expectations (Crudeli *et al*., 2022). These norms motivate individuals to adopt behaviours that align with the majority through social rewards or constraints (Li *et al*., 2021). In this study's case, it was conceptualized that when it comes to agricultural technologies' adoption, rural farmers may have a socially appropriate or inappropriate set of behaviours expected from farmers that may influence their intentions to accept blockchain technology. The injunctive norms would in turn influence the overall attitudes of farmers. For example, in studying the individual's intention to use energy-saving technologies, Ru *et al*. (2018) based on the extended theory of planned behaviour to study intentions of individuals to save energy (use of energy saving technologies) and found that perceived injunctive norms were significantly but negatively correlated with intention to save energy.

Descriptive norms, are formed by the behaviours that most people have engaged in or are engaging in within specific contexts. For instance, when individuals lack sufficient information to make decisions, they often look to the behaviour of others as a guide for their actions. Descriptive norms represent the most commonly observed behaviours that individuals engage in. Given the strong reliance on others' actions, this study posits that descriptive norms can be conceptualized in terms of normative reference groups, which are individuals or groups whose behaviours significantly influence others' actions. In other words, normative reference groups reflect an individual's perception of engaging or not engaging in behaviour relative to others (Turner, 2017). In the context of blockchain technology adoption, the behaviour of peers, groups, or influential figures in society, such as extension agents, local leaders, and farmer group leaders, likely played a role in shaping individual farmers' decisions. Rajanikanth and Gaurav (2023) examined the influence of reference groups on farmers' decisions to purchase tractors in India and found a significant positive impact. Similarly, Zeweld *et al*. (2017) investigated smallholder farmers' intentions to adopt sustainable agricultural practices, drawing on the theory of planned behaviour. Their findings revealed that reference groups had a significant positive effect on farmers' intentions to adopt sustainable practices.

Behavioural sanctions refer to the rewards or punishments that individuals receive for adhering to or violating established social expectations (Cialdini & Goldstein, 2004). In terms of technology adoption, behavioural sanctions can manifest when farmers face social approval (rewards) or disapproval (punishments) based on whether they conform to collective expectations regarding the use or non-use of new technology. For instance, a farmer may receive social support for accepting a new technology, such as blockchain in the barley value chain, or may face disapproval if they do not accept it. This collective reaction from others (whether positive or negative) towards a farmer may influence his or her behavioural intention to accept blockchain.

According to findings from a study carried out in 16 villages in Arua district of eastern Uganda to evaluate the effect of peers on the adoption of mobile-based reporting platforms, social sanctions played a significant role in determining community members' participation in these platforms (Ferrali *et al*., 2020). Their results further suggested that successful technology adoption requires a village rather than an individual. A related study in India (Maertens, 2017) indicated that farmers were discouraged from adopting *Bt* cotton variety due to fear of sanctions from their peers who had had negative experiences with the new variety. The current study aimed to examine the same narrative in the barley value chain of Sebei sub-region in eastern Uganda.

In a nutshell, the adoption of agricultural technologies, such as blockchain, is significantly shaped by social norms. These norms, which are both individual and group-based, exert considerable influence on farmers' attitudes and behaviours. Subjective norms, injunctive norms, normative reference groups, and behavioural sanctions all play a role in determining whether farmers choose to adopt or reject new technologies. Social pressures, whether through perceived approval or disapproval from peers, family, and influential community members, motivate conformity to group expectations. Additionally, normative reference groups and the potential rewards or punishments for adhering to or deviating from social norms further impact technology adoption decisions. This dynamic is especially relevant in collectivist communities like the Sebei sub-region, where social cohesion is highly valued, and individual behaviours are closely tied to group expectations. Therefore, understanding and leveraging social norms is crucial for promoting the successful adoption of blockchain technology and other innovations within agricultural contexts.

**2.4 Determinants of adoption and extent of use of blockchain technology**

In Vietnam, Tran *et al*. (2019) used multinomial endogenous switching regression to analyse the factors that affect adoption of climate smart agricultural technologies. The results indicated that farmer and farmer related characteristics such as gender, age, number of workers, distance to markets, access to climate information, and access to market information had both positive and negative effects on farmers’ decision to adopt climate smart agricultural technologies.

The Fuzzy decision-making trial and evaluation laboratory (Fuzzy DEMATEL) was employed by Maden and Alptekin (2020) to determine the critical factors that affect a company's decision to adopt blockchain in its supply chain. Based on the company requirements, and from the interviews with company experts, the results showed that incorporation of crypto currency, instant money transfer, traceability, smart contracts, immutability, and reduced delays had both negative and positive effects on adoption of blockchain. Fuzzy DEMATEL was appropriate for this analysis since it involved one company which had specific requirements. However, it may not be suitable for cross-sectional data analyses involving many respondents and many variables (Li *et al*., 2023).

In a review study examining the factors affecting adoption of different technologies in India's aquaculture farming, Kumar *et al*. (2018) established that aquaculture farmers' decision to adopt aquaculture related technologies is governed by the productivity, cost efficiency and ease of management of the technology, price of the products and profits from the technology. The extent of adoption however depended on the overall economic, social, regulatory and political factors. As can be observed, there is scarce empirical evidence of blockchain adoption and usage extent in agrifood supply chains, which is why this study contributed towards availing such evidence.

### 2.5 Effect of blockchain technology on barley farmers' productivity and gross margins

Blockchain technology is anticipated to be the future of value chains due to its proven potential in improving the performance of agribusinesses. A review study by Schmidt and Wagner (2019) utilized the transaction cost theory to explore how blockchain technology affects supply chain performance of firms. The findings established that blockchain technology enables transparent and legitimate transactions while reducing opportunistic behaviour among the actors and transaction costs. In a related study, Bhatia *et al*. (2023) employs a context- intervention- mechanism- outcome framework to analyse how blockchain technology influences the performances of four agrifirms in the area of finance sourcing. The findings revealed that blockchain reduces transaction costs related to information search, finance negotiation, and access.

Owing to scarcity of empirical research on farm level productivity and gross margin of last mile smallholder farmers as a result of blockchain technology, Gunasekera and Valenzuela (2020) employed the general equilibrium model based on global economy to project the potential effect of blockchain technology on productivity gains in the Australian grains sector trade. According to their analysis, an expected moderate increase in productivity (5%) brought about by the usage of blockchain in the grains industry could increase output by 8% over the medium term. This finding aligns with that of Firsova and Abrhám (2021) who by conducting enhanced SWOT analysis of blockchain technology implementation in Czech Republic’s agrifood supply chains found that blockchain technology has a potential of directly improving sales of agrifirms.

As noted by Costa *et al*. (2020), information sharing and utilization through blockchain technology improves the crop yields, farmers’ productivity and consequently profitability. This realization was based on an evaluation of a few early use cases of blockchain technology in agrifirms in Uganda, Zambia, London and Indonesia. While studying why some Indian smallholder farmers took up BanQu blockchain technology and others declined, Schoeffel (2019) used Prospective theory and found that farmers took up the technology due to its increased yield and profits attributes. Despite the aforementioned BanQu benefits, the study findings also indicated that a sizeable portion of smallholder farmers in India did not own a mobile phone. This study seeks to find out whether India’s scenario may or may not be true for Uganda.

### 2.6 Identification and prioritizing of blockchain technology implementation challenges

Basing on the unified theory of acceptance and utilization of technology, Yadlapalli *et al*. (2022) used analytic hierarchy process to prioritize the challenges affecting adoption of blockchain technology among the blockchain technology developers, supply chain companies and clients. From their study, blockchain technology complexity, compatibility, organizational structure and external environment were highlighted as critical challenges that required immediate attention for the future success of blockchain technology implementation. As noted, their study was based on high level stakeholders in blockchain development and supply chain companies with limited insights on what challenges the downstream users like smallholder barley farmers would face.

In India and USA, Queiroz and Fosso (2019) used technology extension model estimated by structural equation modelling to highlight blockchain technology adoption challenges at individual levels as opposed to supply chain firms. Differing challenges were identified for India and USA including social influence, inadequate facilitating conditions such as infrastructure and finance, and lack of awareness about blockchain technology. However, Queiroz and Fosso (2019) only highlighted these challenges but did not prioritize them, making it difficult for stakeholders in India and USA’s supply chains to decide on the most effective implementation strategies. This study sought to identify and prioritize the challenges in the context of Uganda’s barley value chain, and solutions were suggested to constitute an adoption framework for decision makers.

Recent systematic reviews have highlighted various blockchain technology implementation challenges across different areas like transport, lands, banking, construction, supply chains, elections, government, and many more. Akram *et al*. (2020), Gao *et al*. (2020) and Nartey *et al*. (2021) mentioned lack of internet connectivity, absence of confidentiality in public permissionless blockchains, resource constraints that hinder availability and scalability, blockchain abuse by hackers due to need for consensus (in crypto currency based blockchain), throughput, latency, and absence of clear regulations and rules in different countries as major implementation challenges. Much as there is surge in literature on blockchain implementation challenges, most of it is done by desk reviews. There is a considerable limitation in empirical studies regarding the same, especially in value chains involving last mile smallholder farmers whose representations in global value chains has been largely ignored. This study seeks to close this knowledge gap.

This study contributes to the expanding body of literature on blockchain technology by providing contextualized insights into Uganda, an emerging economy's efforts to integrate blockchain into crop value chains, particularly among last-mile stakeholders, barley smallholder farmers. While existing research on blockchain adoption has primarily focused on large agribusiness firms and developed economies, this study fills a critical gap by examining its applicability in a smallholder farming context, where challenges such as limited financial resources, low productivity, limited access to inputs, and middlemen exploitation persist. Additionally, the study's attempt to develop a context-based implementation framework offers a foundational background for scaling blockchain adoption across Uganda and the broader region. By addressing the unique socio-economic and institutional factors influencing adoption, this research not only enhances theoretical understanding but also provides practical guidance for policymakers, agribusinesses, and technology developers seeking to promote inclusive and sustainable digital transformation in agriculture.

## 2.7 Theoretical Framework

This study utilized three theories: theory of planned behaviour, unified theory of acceptance and utilization of technology, and random utility theory.

### 2.7.1 Theory of planned behaviour

Developed by Ajzen in 1985, the TPB was an attempt to predict the behaviour of human beings. The theory of planned behaviour is an extension of the theory of reasoned action by

Fishbein and Ajzen in 1975 which mainly missed the component of perceived behavioural control. The Ajzen's theory of planned behaviour is anchored on the postulation that an individual's acceptance of a behaviour (in this case, a barley farmer's use or non-use of blockchain technology) is determined by his or her intentions towards the behaviour. The intentions to use (or not to use) blockchain are in turn determined by a farmer's attitudes, subjective norms and perceived control over the use or non-use of blockchain technology.

Since its development, several applications of the theory of planned behaviour have been put forward by researchers in predicting behaviour across different dimensions. These include among others examining gambling intentions among college students (Wang *et al*., 2021), exam cheating behaviours among university and college students (Hendy & Montargot, 2019), quitting smoking behaviours (Tseng *et al*., 2018), consumers' purchase intentions (Muhammad *et al*., 2022). However, much as the theory of planned behaviour predicts behaviours, most of its aforementioned applications have loosely explained behaviour intentions of individuals in relation to acceptance of technologies such as blockchain. This calls for a more explicit model to enhance the behavioural intentions predictive power of the theory of planned behaviour. The technology acceptance model serves this purpose.

The technology acceptance model was put forward by Davis (1989) with a major purpose of predicting computer usage behaviour, the model has gained popularity in predicting usage behaviour of a wide range of technologies (Marangunić & Granić, 2015; Marikyan *et al*., 2021). The theory of planned behaviour incorporated the technology acceptance model to give psychological insights into how barley farmers behave regarding blockchain technology acceptance. Like the theory of planned behaviour, the technology acceptance model postulates that an individual farmer's behaviour (in this case, blockchain technology acceptance) is determined by their intention to perform the behaviour. The behavioural intention is then in turn determined by the perceived usefulness and perceived ease of use of a certain technology (in this case, blockchain technology) (Davis, 1989).

### 2.7.2 Unified theory of acceptance and utilization of technology (UTAUT)

Exploring the intentions to accept the technology may not be enough if the subsequent use behaviour is not studied. The UTAUT thus combines both acceptance and use of a technology. It was developed by Venkatesh *et al*. (2003) through a review of previous technology acceptance theories with an intention of coming up with a unified acceptance and use theory. The review was based on the highlighted limitations in the previous theories. The UTAUT theory explains user intentions to accept the technology and then subsequent use behaviour (adoption) of the technology. The theory posits that attitudes, subjective norm and behavioural control may implicitly favour intentions but actual use and the extent to which a technology is adopted are largely dependent on other factors. The other factors include performance expectancy, effort expectancy of users, social influence and other facilitating conditions (Hamzat & Mabawonku, 2018). Other authors have attributed continuous use of the technology to satisfaction of the users (Momani, 2020).

Building from the work of Venkatesh and his colleagues, this study adopted some of the factors that underpin the aforesaid four constructs and applied them to the blockchain technology adoption in eastern Uganda's barley value chain context. Such factors include perceived usefulness, ease of use, and relevance of blockchain technology to the barley value chain for performance and effort expectancy (Nikolopoulou *et al*., 2021). The social influence construct for this study included the social norms (both subjective and injunctive), normative reference groups, and group membership (Batucan *et al*., 2022; Bozan *et al*., 2016). While the facilitating conditions construct entailed compatibility, behavioural control factors such as phone ownership, network availability, land ownership, size of land under barley production, and cost benefit related factors (Siswanto *et al*., 2018). The ATAUT theory further allows the inclusion of other farmer factors like gender, age, experience, and use voluntariness which are all vital contributors to examining the adoption and extent of use of blockchain technology in the barley value chain (Marikyan & Papagiannidis, 2023)

**2.7.3 Random utility theory**

The RUT bases on the supposition of rationality. It was developed by McFadden in 1974 and it is grounded on the stochastic preferences whereby the decision maker uses the utility function (value attached to the decision outcome or alternative) to make a choice (Gao *et al*., 2020). The individual being rational, makes decisions basing on the available alternatives, the evaluation factors, and the procedures followed to make the decision, this is referred to as decision dimension (Feather, 2021). The available alternatives in this case were either adopting or not adopting blockchain, the evaluation factors constituted factors that govern the barley farmer's choice such as the of socioeconomic factors and the relative attractiveness of the alternative (Miller, 2020).

The decision procedure entailed calculating the expected outcomes from the choice and weighing them against the expected utility (Martínez, 2018).

In this study's context, barley farmers were expected to be rational in their decision making, and they would choose either to adopt or not adopt blockchain technology based on the utility they derive from this choice. Consequently, barley farmers are expected to make a decision that gives them maximum utility (perceived net benefit). In this case, the utility was productivity and gross margin, derived from adopting or not adopting blockchain technology. The utility for adopting blockchain was given by $Y_{iBCT}$, while the utility for not adopting blockchain technology was given by$Y_{iNBCT}$. Thus, a barley farmer adopted blockchain only if $Y_{iBCT} > Y_{iNBCT}$.

With one main limitation of the random utility theory about the assumption of the error term (which assumes that the preferences must be the same across the sample) (Hess *et al*., 2018), this study maintains this assumption since small scale farmers usually venture into farming with similar goals of increasing their productivity and gross margins. Additionally, in eastern Uganda, barley is mainly grown for supply to the breweries for income generation purposes which further supports the random utility theory assumption of similarity in preferences across the respondents.

**2.8 Conceptual framework**

Based on the theory of planned behaviour, the perceived usefulness of blockchain technology and the barley farmers' perceived ease of use influenced their behavioural intention to adopt blockchain technology. Given the novelty of blockchain, the study also explored the effect of other factors, such as social norms, farmers' image, blockchain's result demonstrability, its relevance to the barley value chain, and voluntariness in acceptance, on the intention to adopt. After examining the behavioural intention, the factors that affect the farmers' decision to adopt and the extent of use of blockchain were also determined and these constituted the independent variables. They included; technological factors, farm, and farmer related factors, and cost benefit related factors.

The dependent variables for the third research question were farmers' productivity and gross margin. Therefore, the adoption of blockchain had either a negative or positive effect on these dependent variables. Productivity and gross margin from the farmers' farms were also affected by a set of farm, farmer and cost benefit related explanatory variables. The challenges impeding blockchain implementation were categorized into 5 criteria, and 12 sub-criteria basing on literature: technology based, farmer based, Company B Company based, middlemen based and regulatory category. The interaction of all these variables is represented in Figure 2.1.

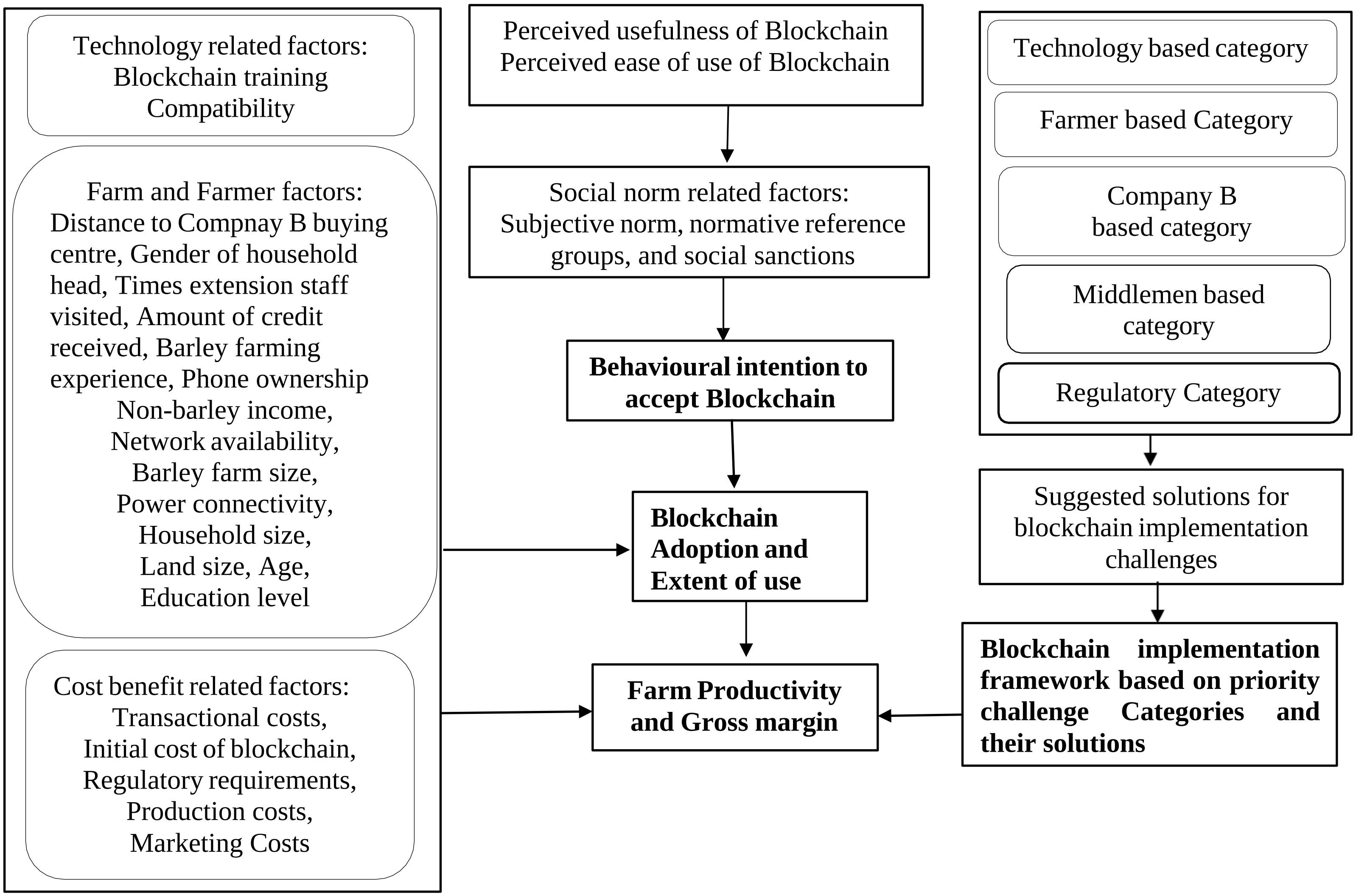


**Figure 2.1:** Conceptual framework for the study

The barley value chain is wide, starting from input providers to end users (beer consumers), but for this study, the analysis was confined to three actors, two of whom have direct interaction with BanQu BCT as described in Figure 2.2.

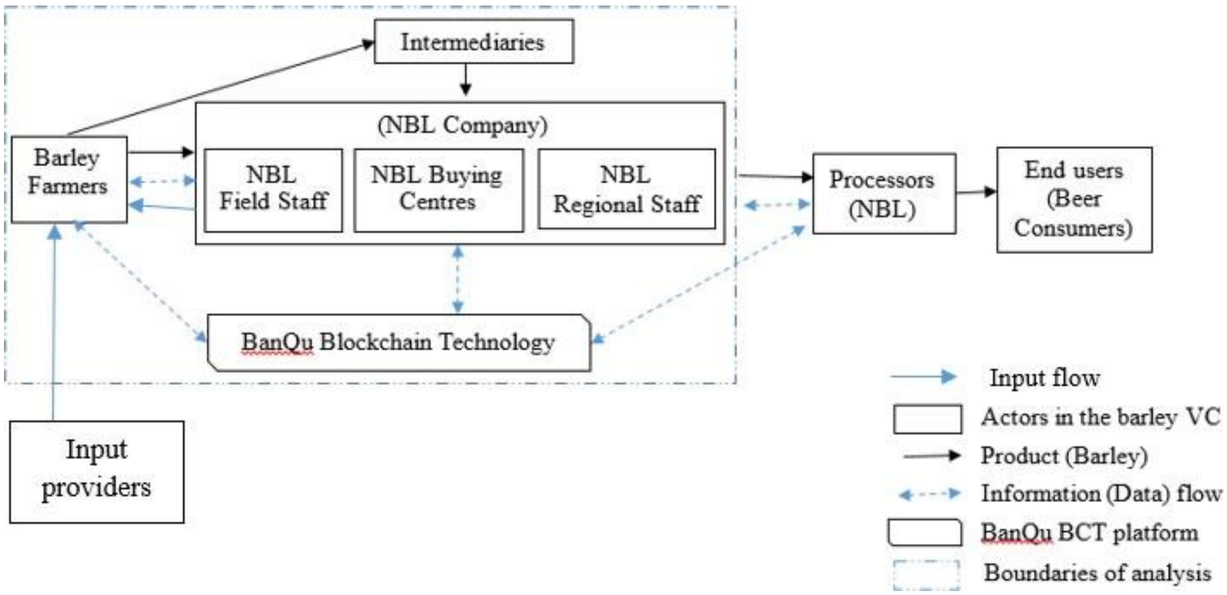


**Figure 2.2:** Structure of the barley value chain studied

# CHAPTER THREE

# RESEARCH METHODOLOGY

This chapter presents the methodologies and materials utilized in the study. It includes a detailed description of the study areas, accompanied by a map, and explains the sampling procedures employed. Additionally, it provides an overview of the data collection methods and the analytical frameworks used to generate the findings.

## 3.1 Study area

The study was conducted in the eastern Uganda's Sebei sub-region, particularly in Bukwo and Kween districts. The two districts are located along the Mount Elgon slopes in the Uganda's eastern border to Kenya. Eastern region was chosen because it produces the most barley in Uganda, while the two districts were chosen because they are the leading producers of barley in eastern region (Cheptoyek, 2018). Furthermore, the districts are located in highland areas of Mt Elgon slopes, which is one of the significant conditions for barley growing.

They have two rainfall seasons, which constitute two growing seasons per year; the first one being March to May while the second one is in August to October. The economic activities in the districts are both crops and livestock production, however, crop production is the most predominant activity. Some examples of livestock reared in these regions are cattle, goats, sheep, and a range of poultry, majorly for home consumption purposes. The food crops grown in the districts are Highland rice, Simsim, Sorghum, Cassava, Beans, and Groundnuts. The cash crops on the other hand are Wheat, Coffee, and barley which is the leading income generating crop with ready market, mainly supply to Company B. The map of the study area is shown in Figure 3.1.

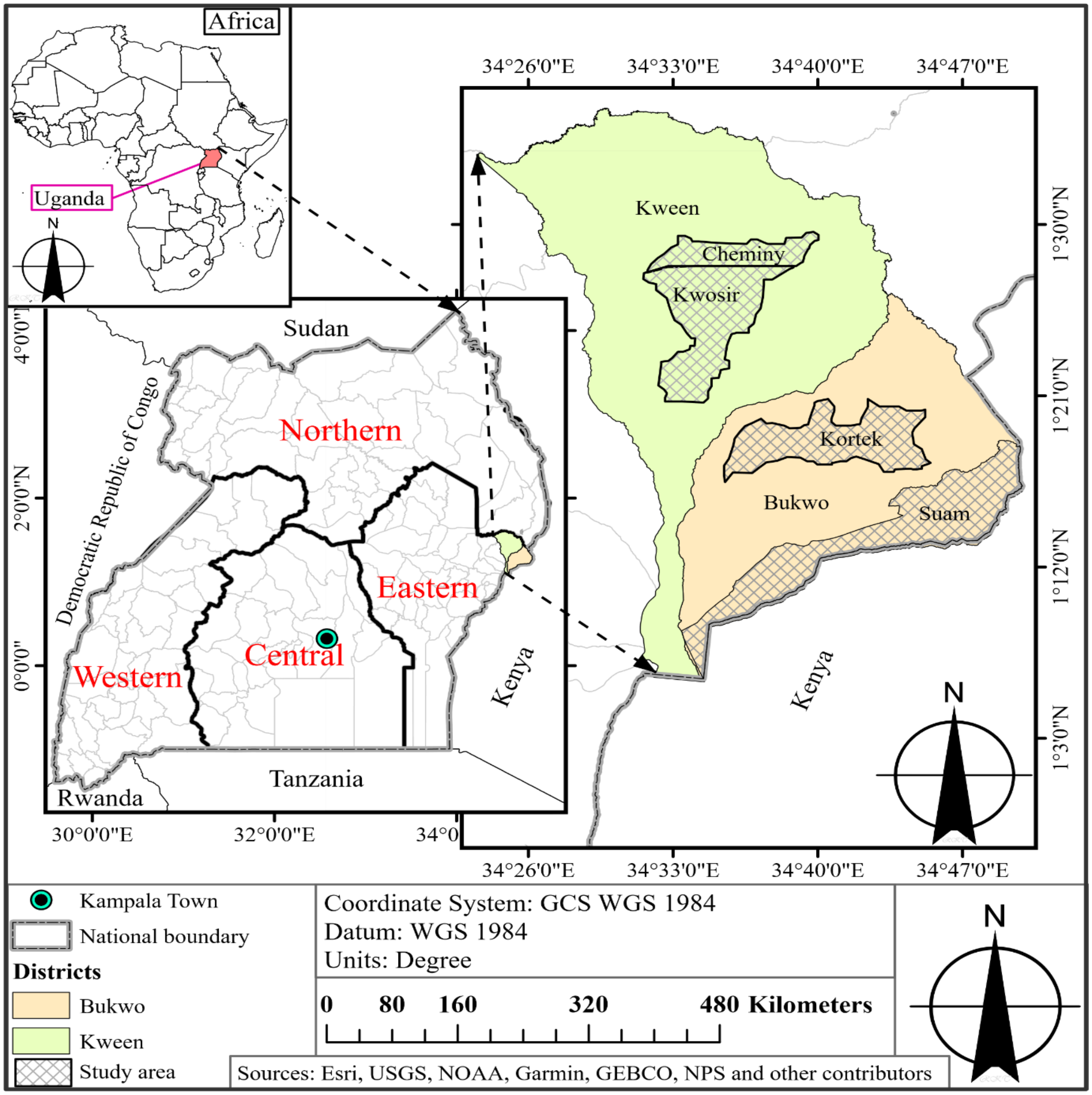


**Figure 3.1:** Map of Uganda showing the study areas

Source: Department of Surveys and Mapping, Uganda (2023)

### 3.2 Research philosophy and approach

A research philosophy is the underlying belief system or perspective that shapes a researcher's approach to conducting research. The philosophy influences the view of the nature of knowledge and reality, and guides decisions on methodology and interpretation (Saunders *et al*., 2019). To this end, the study adopted a pragmatism philosophy because of its flexible approach of mixed methods that encompasses both quantitative and qualitative methods to address the study phenomena (Elgeddawy & Abouraia, 2024). Due to the need to come up with tailored framework of solutions for the challenges affecting blockchain technology implementation in the barley value chain, pragmatism was suitable as it emphasizes practical outcomes and solutions to real world problems, rather than adherence to any single philosophy like positivism or interpretivism (Gillespie *et al*., 2024). As guided by Creswell and Creswell (2018), this pragmatic philosophy served as a foundational element of the research process, and influenced everything from formulating questions to drawing conclusions.

### 3.3 Research design

A mixed-methods design was employed, specifically using an explanatory sequential design, a type of mixed methods design (Creswell & Plano, 2017), to collect both quantitative and qualitative data in sequence. The study began with a survey, where quantitative data were gathered through semi-structured questionnaires. This was followed by qualitative data collection, which involved group discussions and semi-structured interviews with farmer groups and key informants. The explanatory sequential design enabled a deeper exploration of the quantitative findings, offering a broader understanding of the challenges associated with blockchain technology implementation and potential solutions beyond the initial survey responses (Holtrop & Glasgow, 2020). This design was particularly valuable as it allowed the researcher to not only measure outcomes in the quantitative phase but also uncover the underlying reasons and contextual factors that influenced those outcomes.

#### 3.3.1 Study population

The study population included all the barley farmers in Uganda's eastern districts of Bukwo and Kween. The respondents included males and females who are key decision-makers in a household.

#### 3.3.2 Sampling unit

This study's sampling unit were farmers supplying barley to Company B through blockchain technology and those supplying through other channels, in Bukwo and Kween districts. In Bukwo, focus was on the Sub-Counties of Kortek and Suam while in Kween, the focus was on Cheminy and Kwosir Sub-Counties.

#### 3.3.3 Sampling procedure

Bukwo district has 21 sub-counties and 107 parishes, while Kween district has 19 sub-counties and 101 parishes. Given the large number of sub-counties and parishes, a multistage sampling approach was employed, combining both purposive and systematic random sampling techniques to ensure representative data collection while maintaining feasibility (Rahman *et al*., 2022; Ramanujan *et al*., 2022). In the first stage, purposive sampling selected Bukwo and Kween, the two highest barley producing districts in eastern Uganda using information from Company B and District Agricultural Officers.

In the second stage, two sub-counties from each district were purposively selected based on their high barley output and large farming populations. Specifically, Cheminy and Kwosir sub-counties were chosen in Kween district, while Kortek and Suam sub-counties were selected in Bukwo district. In the third stage, two parishes were purposively selected from each sub-county, again based on their significant barley production and farmer population, making a total of 8 parishes. The selected parishes were Chesimat and Kubobei in Kortek sub-county; Suam and Kaptererwa in Suam sub-county; Serere and Kamwam in Cheminy sub-county; and Kere and Tuikat in Kwosir sub-county. In the fourth stage, purposive sampling divided the farmers in the selected parishes into two categories of blockchain technology adopters and non-adopters. This was aided by farmers' lists obtained from Sub-County Agricultural Officers and Company B field officers.

In the fifth stage, probability proportional to size sampling was used to select 491 respondents, as the parishes varied in size. This sampling approach combined systematic random sampling with purposive selection to ensure equal representation of blockchain adopters and non-adopters from the parishes, with each group contributing half of the sample. Although the two were not individually matched, this approach allowed for comparability across the two groups. To ensure randomization in the final selection of respondents, systematic random sampling was used to distribute the sample across the selected parishes (Mostafa & Ahmad, 2018).

Farmer lists from Company B field officers provided the number of farmers by category per parish. Then, the sampling interval ($K$) was calculated as $K = N/n$, where $N$ is the number of farmers in a given parish and $n$ is the sample size assigned to that parish. Given the variability in parish sizes, the sampling interval differed across parishes. Finally, a random starting point was selected within each parish using simple random sampling, and then every K-th farmer was chosen until all 245 questionnaires were administered

### 3.3.4 Sample size determination

Sample size was determined using the probability proportional to size sampling process described by Cochran (1963), as shown below:

$$n = \frac{z^2pq}{e^2} \quad (1)$$

where; *n* is sample size, *p* is the proportion of the population containing the famers of interest, *q* as the weighting variable is given as 1-*p*, while *z* is the possible maximum variance in the population estimated basing on the confidence level (α=0.96). *e* is the acceptable error (0.04) and according to Kothari (2004), the error of less than 10% is typically acceptable. Since the variation of the targeted barley farmers was not be known prior to the survey, *p* for this study was assumed at 0.5 (*p*=0.5) which is 50% of the barley farmers, while the z score value was 1.75 based on the 0.04 confidence level, thus the *q* was 0.5 *(*from 1- 0.5). The sample was calculated as:

$$n = \frac{(1.75^2)(0.5)(0.5)}{0.04^2} = 478.51 \sim 479 \quad (2)$$

However, during data collection, over-sampling was intentionally done to account for possible incomplete, or inconsistent questionnaires, a common practice in field surveys to safeguard the minimum target sample size (Dillman *et al*., 2014). In total, 500 respondents were reached, ensuring that even after data cleaning and quality checks, a robust and statistically valid dataset would be retained. Ultimately, 491 responses met the inclusion criteria and were deemed suitable for analysis, slightly exceeding the proposed number of 479. This outcome enhanced the precision and reliability of the results without compromising methodological rigor, as the same sampling procedures and inclusion criteria outlined in the proposal were strictly followed.

Additionally, 2 group discussions, each composed of a minimum of 10 barley farmers was conducted to provide additional data. The 2 group discussions were held in the 2 districts of Bukwo and Kween, selecting 1 group discussion from each district. Key informant interviews were also carried out with 10 stakeholders in the barley value chain to further provide data for the study. The key informants included: 2 Company B mid-level managers, 3 Company B field staff (2 extension and 1 staff at buying centre), and 3 middlemen. Table 3.1 shows the distribution of farmers selected from each district and each parish following probability proportional to size sampling.

**Table 3.1:** Sample size distribution in each sub-county across the two districts

| District | Sub-County | Parish | Percentage contribution to total sample (%) | Sample |
|---|---|---|---|---|
| Bukwo | Kortek | Chesimat | 10 | 49 |
| | | Kubobei | 15 | 75 |
| | Suam | Suam | 11 | 53 |

| | | | | |
|---|---|---|---|---|
| | | Kaptererwa | 14 | 68 |
| Kween | Cheminy | Serere | 10 | 49 |
| | | Kamwam | 10 | 49 |
| | Kwosir | Kere | 15 | 74 |
| | | Tuikat | 15 | 74 |
| Total | 4 | 8 | 100 | 479 |

Source: Bukwo and Kween Districts Agricultural Officers, 2023; Company B records,

**3.3.5 Data sources, data collection tools, and methods**

The study employed both quantitative and qualitative primary data. Quantitative data was collected through face-to-face surveys with farmers, using semi-structured questionnaires administered by trained enumerators. The questionnaire covered various aspects, including household and barley farm characteristics and respondent demographics. It also featured item scale measurements of the second extension of the technology acceptance model and the social norm analysis constructs to address the first research objective, factors influencing blockchain adoption and its extent for the second objective, and the effect of blockchain technology on productivity and gross margin for the third objective. Additionally, farmers were asked to identify the challenges affecting blockchain technology implementation, and suggest solutions.

Qualitative data was gathered through semi-structured interviews with farmer groups (group discussions) and key informants, specifically stakeholders in the barley value chain. Data collection methods included audio recording, note-taking, and participant observation. Group discussions and key informant interviews focused on identifying and prioritizing challenges related to blockchain technology implementation, as well as exploring potential solutions to address the fourth objective.

Before data collection, the research underwent a thorough ethical review and was approved by the ethics committees of the two Universities: Egerton University, Approval No. EUISERC/APP/355/2024), and Uganda Christian University, Approval No. UCUREC-2024-1000). Furthermore, the study received approval from Uganda's National Council for Science and Technology, Registration No. A536ES, to be conducted in the designated region (Eastern Uganda's Sebei sub-region). To uphold voluntary participation, farmers selected for the study were provided with consent forms before each interview, enabling them to formally consent to their involvement.

### 3.4 Validity and reliability

Prior to data collection, a two-day training session was conducted for five enumerators to familiarize them with the tools, guide them on ethical conduct, and ensure they could effectively ask questions to elicit the desired responses. The validity and reliability of the data collection tools were ensured by conducting a pre-test study in one Sub-County, Kitawoi (not included in the sample). A total of 48 questionnaires were administered to the respondents prior to the actual study. This constituted 10% of the actual sample size as recommended by Abegunde *et al*. (2020). The data from the pre-test was then used to run Cronbach alpha reliability coefficient to check whether it was 0.7 and above as recommended by Taber (2018). The collected data was then used to update the final tool so that the data obtained from the final survey would match the purported data, and could be obtained from repeated trials of the same study as recommended by Rose and Johnson (2020).

### 3.5 Data analysis

The data were analysed using both descriptive and inferential statistics. Smart-PLS version 4 was used to analyse objective 1, STATA version 17 was employed for objectives 2 and 3, and XLSTAT version 19 was utilized for objective 4.

### 3.6 Analytical framework

#### 3.6.1 Determining barley farmers' behavioural intention to accept Blockchain technology

For the first objective, the outcome variable was behavioural intention to accept blockchain technology (BI) while the explanatory variables were perceived usefulness (PU) and perceived ease of use (PEU). Due to the nature of these variables, analysis was based on the theory of planned behaviour, and technology acceptance model. However, due to novelty of blockchain, perceived usefulness and perceived ease of use may not necessarily underpin farmers' intention to use, or later on predict potential acceptance of blockchain technology (Marangunić & Granić, 2015). There is need therefore to understand the antecedents of farmers' perceptions, especially regarding blockchain technology usefulness. Ease of use may not hold so much for this study since farmers are assumed not to have much interaction with the blockchain technology except for receiving SMSs upon transacting. Therefore, only perceived behavioural control was considered to underpin ease of use.

The antecedents of perceived usefulness such as subjective norm (SUN), farmer attitudes (FA), farmer image (FI), blockchain relevance to barley value chain (BR), blockchain results' demonstrability (BD), and the moderating variables of perceived barley output quality (BQ) and voluntariness in accepting blockchain technology (BV) was explored. These were incorporated in the original technology acceptance model to constitute the second extension of technology acceptance model (Ngubelanga & Duffett, 2021; Salloum *et al*., 2019). The independent variables were hypothesized to have a positive influence on the dependent variables stated in the hypotheses. The conceptual model is given in Figure **3.2**.

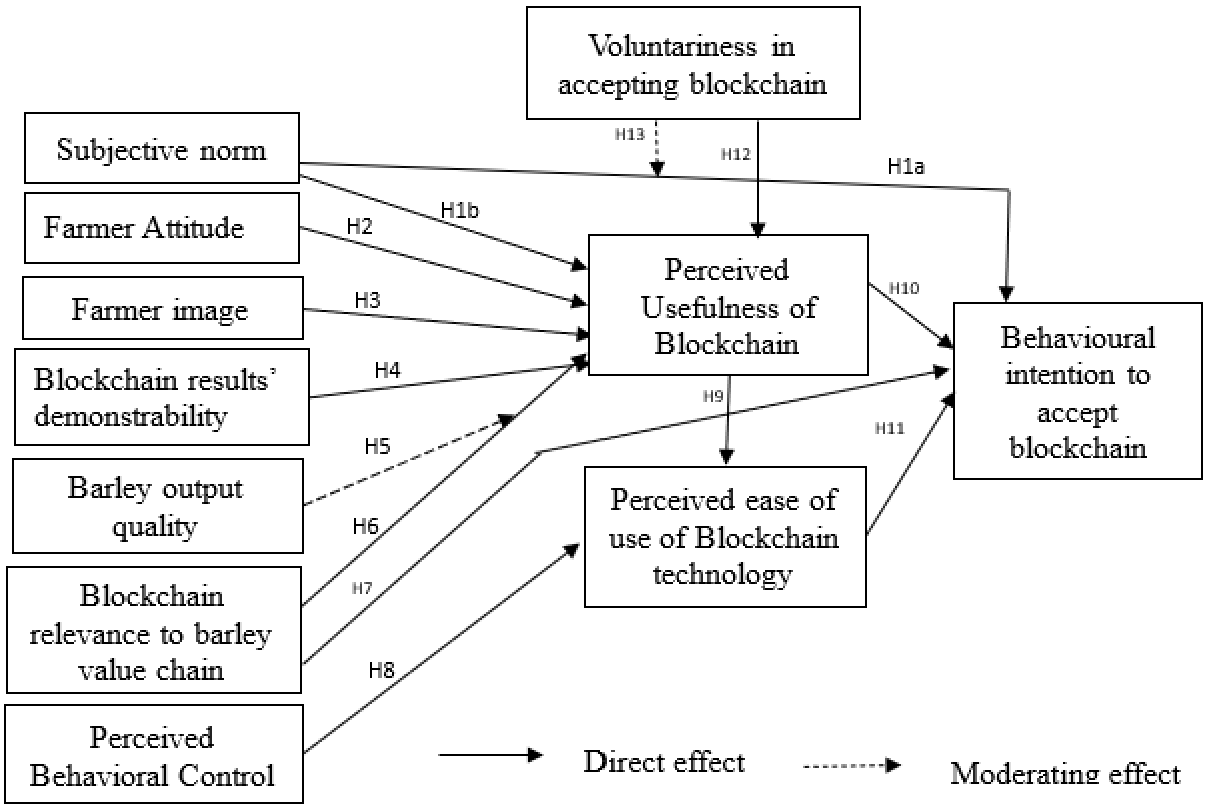


**Figure 3.2:** Proposed research model of farmers' behavioural intention to accept blockchain technology

Source: Adapted from Davis and Venkatesh (2000)

The following hypotheses were tested:

H1a: Subjective norm (SUN) significantly and positively influences Behavioural intention (BI) to accept blockchain technology

H1b: Subjective norm (SUN) significantly and positively influences Perceived usefulness (PU) of blockchain technology

H2: Farmer attitude (FA) has a significant and positive effect on Perceived usefulness (PU) of blockchain technology

H3: Perceived farmer image (FI) has a positive and significant influence on perceived usefulness (PU) of blockchain

H4: Barley value chain results' demonstrability (BD) as a result of using blockchain technology has a positive and significant effect on perceived usefulness of blockchain technology

H5: Barley output quality (BQ) has a significant and positive moderating effect on the relationship between blockchain technology relevance to barley value chain (BR) and perceived usefulness (PU) of blockchain technology

H6: Blockchain technology relevance to barley value chain (BR) has a positive and significant effect on perceived usefulness (PU)

H7: Blockchain technology relevance to the barley value chain (BR) has a positive and significant effect on behavioural intention (BI) to accept blockchain technology.

H8: Perceived behavioural control (PBC) significantly and positively affects perceived usefulness of blockchain technology

H9: Perceived ease of use of blockchain technology (PEU) significantly and positively influences perceived usefulness (PU) of blockchain technology

H10: Perceived usefulness of blockchain technology positively and significantly influences behavioural intention (BI) to accept blockchain technology.

H11: Perceived ease of use (PEU) has a positive and significant effect on behavioural intention (BI) to accept blockchain technology.

H12: Voluntariness to accept blockchain technology (BV) significantly and positively influences perceived usefulness of blockchain technology (PU)

H13: Voluntariness to accept blockchain technology positively and significantly moderates the relationship between subjective norm and behavioural intention (BI)

### 3.6.2 Hypotheses tested in the social norm analysis

Barley is grown in the rural areas of Uganda where social norms play a big role in the behavioural orientations of people. There is need to understand further how social norm affects acceptance of blockchain technology in the study area. Social norms are a set of shared acceptable standards of beliefs, attitudes, and behaviour by groups of people. A farmer does not exist in isolation, but exists with either fellow farmers (person-to-person) or among the groups of farmers (person-to group) whose perceptions may influence his or her behavioural intentions. Deriving from Costenbader *et al.* (2019), Hüttel *et al*. (2022) and Pérez-Sánchez *et al*. (2021), the relevant variables for measuring social norms for this study were other people's attitudes/beliefs towards the farmer's acceptable behaviour (Injunctive norm), normative reference groups, behavioural sanctions which influence a farmer's attitude towards accepting blockchain technology. They were hypothesized to have a positive effect on intention to accept blockchain technology. The conceptual model is presented in Figure 3.3.

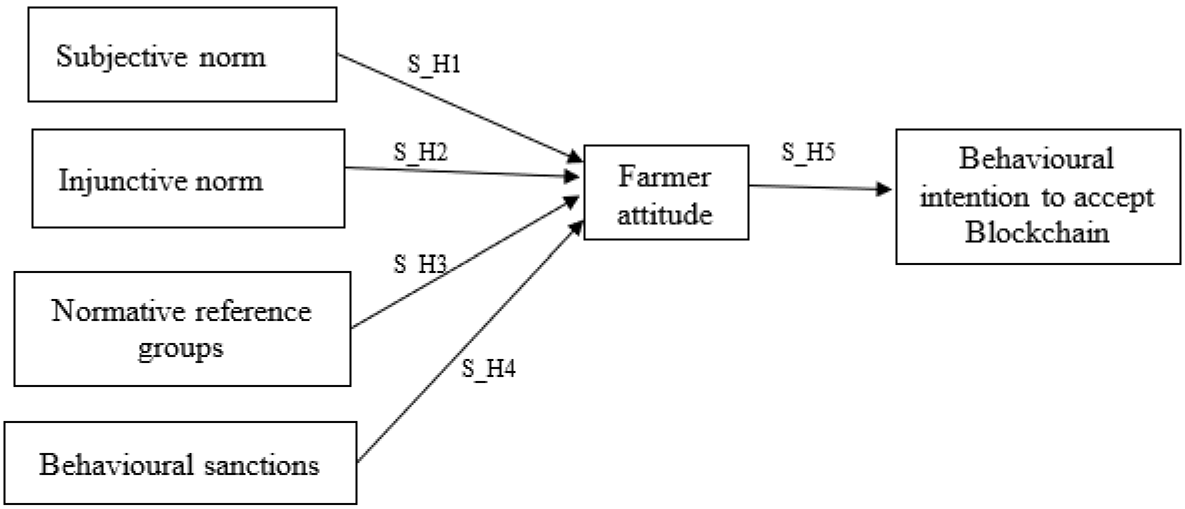


**Figure 3.3:** Conceptual model for social norms' effect on farmer acceptance of blockchain technology

S_H1: Subjective norm has a positive and significant effect on farmer attitude

S_H2: Injunctive norm has a positive and significant effect on farmer attitude

S_H3: Normative reference groups have a positive and significant effect on farmer attitude

S_H4: Behavioural sanctions have a positive and significant effect on farmer attitude

S_H5: Farmer attitude has a positive and significant effect on behavioural intention to accept blockchain technology

Due to multiple variables and factors affecting the variables, this study modelled the second extension of technology acceptance model, and social norm analysis using partial least squares structural equation modelling to determine farmers' behavioural intention to accept blockchain technology. The partial least squares structural equation modelling was preferred because of its wide applicability in empirical studies of human and social behaviour, higher prediction capacity and ability to use reflection on observed constructs (Manley *et al*., 2021; Shmueli *et al*., 2019). Description and measurement of variables to be used in analysing objective one are shown in Table

3.2 All variables were measured on a 5-point Likert scale: 1= Strongly disagree, 2= disagree, 3= Neutral, 4= Agree, 5= Strongly agree.

**Table 3.2:** Variables in the second extension of technology acceptance model and social norm analysis

| Variables | Description | Measurement | Hypothesis sign | Literature source |
|---|---|---|---|---|
| **Dependent Variable** | | | | |
| Behavioural Intention (BI) | A farmer's subjective probability that he or she would accept to use blockchain | 5-point Likert scale | +/- | Ajzen, (1996); Fishbein & Ajzen, (1975); Ajzen, (1991) |
| **Independent Variables** | | | | |
| Perceived usefulness (PU) | The extent to which a farmer believes that employing blockchain technology would improve his or her barley farm performance | 5-point Likert scale | +/- | Davis, (1989); Marikyan *et al*., (2021) |
| Perceived ease of use (PEU) | The extent to which a farmer believes that using blockchain would be effortless | 5-point Likert scale | +/- | Davis, (1989); Marikyan *et al*., (2021) |
| Subjective norm (SUN) | The farmer's perception of what other people important to him or her want him or her to do regarding blockchain technology use | 5-point Likert scale | +/- | Venkatesh *et al*., (2003); Batucan *et al*., (2022); Wang *et al*., (2019) |
| Farmer attitude (FA) | The farmers' positive or negative beliefs and or feelings regarding use of blockchain | 5-point Likert scale | +/- | Davis, (1989); Dong *et al*., (2022) |
| Farmer image (FI) | The degree to which BCT use is perceived to enhance a farmer's status in society. | 5-point Likert scale | +/- | Moore & Benbasat, (1991); Bashir *et al*., (2022) |
| Blockchain relevance to barley value chain (BR) | Farmers' perception concerning the degree to which blockchain technology is applicable in the barley value chain | 5-point Likert scale | +/- | Venkatesh & Davis, (2000); Nikolopoulou *et al*., (2021); Okcu *et al*., (2019) |

| | | | | |
|---|---|---|---|---|
| Barley output quality (BQ) | The degree to which a farmer believes that blockchain use improves barley quality | 5-point Likert scale | +/- | Venkatesh & Davis, (2000); Moreno *et al*., (2017) |
| Blockchain result demonstrability (BD) | Farmers' perception on the tangibility of the results of using blockchain in barley value chain activities | 5-point Likert scale | +/- | Soodon *et al*., (2024); Dai & Cheng, (2022); Venkatesh & Davis, (2000) |
| Voluntariness in accepting blockchain (BV) | The degree to which farmers perceive blockchain technology adoption decision to be non-mandatory | 5-point Likert scale | +/- | Park *et al*., (2022); Venkatesh & Davis, (2000) |
| Perceived Behavioural control (PBC) | The farmers' perception of whether they have the capacity and control over the use of blockchain technology | 5-point Likert scale | +/- | Ajzen, (1985); Lopes *et al*., (2024) |
| Injunctive norm (IN) | Other people's (society's expectations) perception of what a farmer should do regarding using blockchain | 5-point Likert scale | +/- | Batucan *et al*., (2022); Bozan *et al*., (2016). Nystrand & Olsen, (2020) |
| Normative reference groups (NRG) | The perception of a farmer's blockchain use or non-use behaviour in comparison with other stakeholders, groups or individual farmers | 5-point Likert scale | +/- | Pfeiffer *et al*., (2021); Zeweld *et al*., (2019); Mishra *et al*., (2024b) |
| Behavioural sanctions (BS) | The reaction from other people, groups, or individual farmers towards a farmer's blockchain use or non-use behaviour | 5-point Likert scale | +/- | Zinngrebe *et al*., (2017); Liu *et al*., (2018) |

### 3.6.3 Determining the factors that influence adoption and extent of use of blockchain technology

In this second objective, the outcome variables were farmer's decision to adopt and extent of use of BCT. Decision to adopt is binary (*1=Adopter; 0= Non-adopter*), while extent of use outcome is continuous (i.e. *Number of seasons BCT was used in the production and supply of barley from the time of introduction in 2019 to the survey period*). Because of the binary and continuous nature of the outcome variables, double hurdle model (DHM) was used to analyse this objective in two separate stages (Cragg, 1971). Although Tobit and Two-step Heckman model could be used, they have some drawbacks. Tobit assumes that the two stages are modelled in a single equation, are affected by the same set of variables, and that variables have the same direction of influence on the outcomes in the two stages (Cherotich *et al*., 2022; Workineh *et al*., 2020) which may not be true in practice.

Heckman model on the other hand, is basically a selection bias-based model which uses the inverse mills ratio to correct for bias in non-randomly selected samples, yet this study's assumption is that the sample was randomly selected. In addition, Heckman regards zero responses in the first stage as unobserved due to missing variables (Mignouna *et al*., 2017), implying that in the second stage, number of seasons blockchain technology was used in the production and supply of barley to Company B was only recorded in the adopters only. This too may not be appropriate since a farmer may deliberately choose not to adopt blockchain technology in the first stage. Using Heckman would thus limit the farmers from exercising their optimal decision of whether to adopt the BCT or not (Swaumu *et al*., 2022).

The Double Hurdle model remains the most appropriate for this objective because it analyses the two decisions separately, unlike Tobit, and permits the zero cases in both stages, attributing them to randomness and the farmer's optimal decision, unlike Heckman (Cherotich *et al*., 2022). The Double Hurdle model assumes that individual farmers pass through these hurdles differently to assume maximum satisfaction. The two hurdles were dependent on a set of technological, farm and farmer characteristics, and cost benefit variables as shown in Table 3.3 The equations for the first and second stages were modelled by binary Probit and censored Tobit respectively, as specified by Ayuya (2010) and Cherotich *et al*. (2022). The first stage equation is shown below:

$T_i^* = x_i'\beta + u_i, \qquad u_i \sim N(0,1)$ Decision to adopt blockchain technology (3)

so that $T_i^* = \begin{cases} 1, & if\ T_i^* > 0 \\ 0, & otherwise \end{cases}$

where $T_i^*$ is the latent variable for $T_i$ representing blockchain technology adoption when $T_i^* = 1$ and non-adoption of blockchain when $T_i^* = 0$, $x_i'$ is the vector of explanatory variables, $\beta$ is a vector of coefficients to be estimated, and $u_i$ is the error term which follows an independent normal distribution

in the second stage, where by only the farmers with the adoption outcome greater than 0 ($y_i^* > 0$) was observed, the model is specified as below:

$y_i^* = z_i'\beta + v_i, \qquad v_i \sim N(0, \sigma^2)$ Extent of use of blockchain technology (4)

So that $y_i = \begin{cases} y_i^*, & if\ y_i^* > 0; and\ y_i = 1 \\ 0 & Otherwise \end{cases}$

where $y_i$ is the observed number of seasons blockchain technology was used in the production and supply of barley when $y_i^* > 0$, for those farmers not adopting blockchain $y_i = 0$, $z_i'$ is the vector of explanatory variables, $\beta$ is a vector of coefficients to be estimated, and $v_i$ is the error term which follows an independent normal distribution.

Integrating the two stages gives the following models

$$\left.\begin{aligned} T_i &= x_i'\beta + \mu_i \text{ If } T_i^* > 0, \text{ and } = 0 \text{ if otherwise} \\ y_i &= z_i'\beta + v_i \text{ If } y_i^* > 0, \text{ and } = 0 \text{ if otherwise} \end{aligned}\right\} \qquad (5)$$

The empirical model for farmer's decision to adopt BCT (first stage) was given as

$$BCTadopt = \beta_0 + \beta_1 sex + \beta_2 age + \beta_3 education + \beta_4 Age + \beta_5 marital\_status + \beta_6 extensionfreq + \beta_7 grpmembshp + \beta_8 BCTtrain\_cost + \beta_9 netwk\_connect + \beta_{10} prod\_cost + \beta_{11} powr\_connect + \beta_{12} land\_tenure + \beta_{13} dist\_NBL + \beta_{14} land\_size + \beta_{15} BCTinitial\_cost + \beta_{16} BCTcompat + \beta_{17} extension\_costs + \beta_{18} mkng\_costs + \beta_{19} phone\_own + u_i \qquad (6)$$

The empirical model for the second equation was given as:

$$Number\ of\ seasons\ of\ BCTuse = \beta_0 + \beta_1 sex + \beta_2 age + \beta_3 education + \beta_4 Age + \beta_5 marital\_status + \beta_6 extensionfreq + \beta_7 grpmembshp + \beta_8 BCTtrain\_cost + \beta_9 netwk\_connect + \beta_{10} prod\_cost +$$

$\beta_{11}powr\_connect + \beta_{12}land\_tenure + \beta_{13}dist\_NBL + \beta_{14}land\_size +$
$\beta_{15}BCTinitial\_cost + \beta_{16}extension\_costs + \beta_{17}mkng\_costs + \beta_{18}phone\_own + u_i$

(7)

In order to allow for heteroskedasticity and the non-normal error, the log-likelihood function for the DHM ($LL_{DHM}$) in the first and the second stage was specified as follows (Kasase *et al*., 2022):

$$LL_{DHM} = \sum_0 ln\,[1 - \Phi(Z_i\alpha)\Phi\,(\frac{x_i'\beta}{\sigma_i})] + \sum_+ ln\,[\Phi(Z_i\alpha)\,\frac{1}{\sigma_i}\phi\,(\frac{y_i - x_i}{\sigma_i})] \qquad (8)$$

where, $\Phi$ and $\phi$ are probability density function (PDF) and cumulative density function (CDF) of the first and second stage respectively.

Additionally, to determine the effect of explanatory variables on extent of blockchain technology use, marginal effects from the log-likelihood estimation results of the double hurdle model was calculated following Jensen and Yen (1996).

$$(y_i/y_i > 0) = \Phi\,(\frac{x_i'\beta}{\sigma_i})^{-1}\int_0^\infty (\frac{y_i}{\sigma_i\sqrt{1+\theta^2 y_i^2}}\Phi\,(\frac{T(\emptyset y_i) - x_i'\beta)}{\sigma_i}))\,dy_i \qquad (9)$$

**Table 3.3:** Variables used in the Double Hurdle Model

| Variables | Description | Measurement | | |
|---|---|---|---|---|
| **Dependent variables** | | | | |
| BCT adoption | Blockchain technology adoption status | Binary (1=adopt, 0=otherwise) | | |
| Number of seasons | Seasons of blockchain use in the barley value chain since 2019 | Continuous (Number of seasons) | | |
| **Explanatory Variables** | | | **Expected sign** | **Source of literature** |
| Sex | Sex of the farmer | Binary (1=Male, 0=Female) | +/- | Tran *et al*., (2019); Neway & Zegeye (2022) |
| Age | Age of the farmer in years | Continuous | +/- | Tran *et al*., (2019); Boufous *et al*., (2023) |
| Education level | Number of years in school | Continuous | + | Sendros *et al*., (2022); Krithika & Zareena (2022) |
| Marital status | Farmer's marital status | Binary (1=Married, 0=Single) | +/- | Atube *et al*., (2021); Badstue *et al*., (2020) |
| Extension services | Number of agricultural extensions visits in a year | Continuous | + | Chelang'a *et al*., (2023); Pan *et al*., (2018) |
| Blockchain training | Number of blockchain tailored trainings in a year | Continuous | + | AlShamsi *et al*., (2022); Silva *et al*., (2024) |
| Phone ownership | Phone ownership by a farmer | Binary (1=Yes,0=No) | + | Akella *et al*., (2023); Khan *et al*., (2022) |

| | | | | |
|---|---|---|---|---|
| Group membership | A farmer belonging to a group or not | Binary (1=Yes. 0=No) | + | Nandhini *et al*., (2023) |
| Blockchain training cost | The total costs in of accessing blockchain training by a farmer | Continuous (USD) | - | Chakraborty & Paul (2023) |
| Network connectivity | Stability of the mobile phone network | Binary (1=Stable, 0=Unstable) | + | Alammary *et al*., (2019) |
| Production costs | Total cost pertaining barley production | Continuous (USD) | + | Chiaraluce *et al*., (2024) |
| Power connection | Whether a farmer is connected to power or not (grid/solar) | Binary (1=Connected, 0=Not connected) | + | Peters *et al*., (2019) |
| Land tenure | The form of ownership of land | Binary (1=Customary, 0=Commercial) | - | Toader *et al*., (2024) |
| Distance to buying centres | Farm/household distance in Kilometres to Company B barley buying centre | Continuous (Km) | - | Tran *et al*., (2019); Li *et al*., (2024) |
| Size of land owned | Total size of land owned by the farmer | Continuous (Acres) | + | Temesgen & Aweke (2023); Emran *et al*., (2021) |
| Phone compatibility | Phone compatibility with the blockchain app and other existing systems | Binary (1=Yes, 0=No) | + | Choi *et al*., (2020); Ullah *et al*., (2021) |
| Extension services costs | Total costs for accessing extension services | Continuous (USD) | - | Pan *et al*., (2018); Tu *et al*., (2018) |
| Marketing costs | Total costs pertaining barley marketing | Continuous (USD) | + | Kumar *et al*., (2018) |
| Blockchain initial cost | Initial cost for enrolling the farmer on blockchain app | Continuous (USD) | - | Masi *et al*., (2022); Mishrif & Khan (2023) |

### 3.6.4 Determining the effect of blockchain technology on barley farmers' productivity and gross margin

In the third objective, the outcome variables were productivity and gross margin of the farmers in the two categories (blockchain adopters and non-adopters) as a result of a treatment variable (blockchain technology), while the explanatory variables were cost benefit, farm and farmer related factors. Attributing the difference in productivity and gross margin between the two groups to blockchain technology is rather basic and biased, as counterfactual situations cannot be observed in cross-sectional data as in the experimental design (Danso-Abbeam *et al*., 2021). This can make causal inference problematic, thus requiring a model which can analyse both the observed and counterfactual in respect to blockchain adoption and its effect on productivity and gross margin.

There are two models that could possibly analyse this objective: Propensity Score Matching and Endogenous Switching Regression (ESR) model. The former has drawbacks; it does not account for unobservable characteristics behind farmers' decision to adopt or not adopt blockchain technology, which later effect their productivity and gross margin. The other one is the selection bias problem and endogeneity (of simultaneous type). Selection bias arises whereby farmers may self-select themselves into adopting blockchain technology, while simultaneous endogeneity arises whereby farmers may possess inherent characteristics such as aggressiveness, risk averse, that correlate with those of variables affecting productivity and gross margin (Rosenbaum & Rubin, 1983). To cater for the drawbacks, ESR was appropriate since it controls for both observed and unobserved characteristics and eliminates sample selection bias (Kanburi *et al*., 2019).

Productivity was measured in terms of yield (in kilograms, Kgs) divided by number of hectares; while gross margin was measured by subtracting total variable costs from total revenue.

$$GM_i = TR_i - TVC_i \tag{10}$$

where, *GM* denotes Gross Margin*; TR* denotes Total Revenue; *TVC* denotes Total Variable Cost; while *i* denotes farmer 1,2,..*n* for either *BCT* adopting or non-adopting farmers.

The ESR model followed two steps: the first is a selection equation, and use Probit regression to model the decision to adopt (or not to adopt) blockchain technology based on the random utility theory of rationality in decision making. Farmers would adopt blockchain technology only if the choice gives them maximum net perceived benefit/utility in terms of productivity and gross margin, $Y_{iBCT} > Y_{iNBCT}$. Apart from the observed characteristics, inherent variables were unknown/latent, the utility derived from such variables was denoted as $L_i^*$, and expressed as a function of the explanatory observable characteristics, denoted as $Z$ in a latent variable model:

$$L_i^* = Z_i\gamma + \varepsilon_i; \qquad L_i = 1 \text{ if } L_i^* > 0; \; L_i = 0 \text{ if } L_i^* \leq 0 \tag{11}$$

where, $L_i^*$ is the unobservable utility, $\gamma$ is the coefficients to be estimated (a barley farmer would adopt BCT only if the coefficients (net perceived benefits) are positive), $L_i$ is dummy, 1=adopters, 0= otherwise, while $\varepsilon_i$ is the error terms assumed to be independent and normally distributed.

In the second step, the effects of blockchain technology on productivity and gross margin was estimated basing on whether a farmer was a blockchain technology adopter or non-adopter. The equations are called regime equations and are specified as follows:

Blockchain adopting farmers $Y_{iBCT} = X_{iBCT}\beta_{BCT} + u_{iBCT}$ (12)

Blockchain non-adopting farmers $Y_{iNBCT} = X_{iNBCT}\beta_{NBCT} + u_{iNBCT}$ (13)

where $Y_{iBCT}$ and $Y_{iNBCT}$ are outcome variables, $X_{iBCT}$ and $X_{iNBCT}$ are vectors of explanatory variables, $\beta_{BCT}$ and $\beta_{NBCT}$ are the parameter estimates in both regimes while $u_{iBCT}$ and $u_{iNBCT}$ are independent and identically distributed error terms. The explanatory variables in $X_{iBCT}$ and $X_{iNBCT}$ should be contained in $Z_i$ in equation 11, implying that $Z_i$ must include at least one more variables not included in the equations 12 and 13; blockchain related training, group membership and distance to Company B buying centres were the instrumental variables added in $Z_i$. The error terms in the selection equation and the regime equations ($\varepsilon_i$, $u_{iBCT}$, and $u_{iNBCT}$) were assumed to have covariance matrix and a trivariate normal distribution with zero mean vectors as shown below:

$$Cov(\varepsilon_i, u_{iBCT}, u_{iNBCT}) = \begin{bmatrix} \sigma^2_{\varepsilon_i} & \sigma_{\varepsilon_{iNBCT}} & \sigma_{\varepsilon_{iBCT}} \\ \sigma_{\varepsilon_{iBCT}} & \sigma^2_{iNBCT} & \sigma_{iNBCTiBCT} \\ \sigma_{\varepsilon_{iNBCT}} & \sigma_{iNBCTiBCT} & \sigma^2_{iBCT} \end{bmatrix} \tag{14}$$

Since the unobserved explanatory variables that affect the farmer's choice to adopt blockchain also affect productivity and gross margin in both regimes, it is important to analyse both the selection step and the regime step simultaneously. For this to be possible, a full information maximum likelihood estimation was used with the ESR model. The conditional and the unconditional productivity and gross margin expectations from the blockchain technology adopters and non- adopters were calculated based on the estimated parameters of $\beta_{BCT}$ and $\beta_{NBCT}$. The counterfactual productivity and gross margin were not observable, but were estimated through the $\beta_{BCT}$ and $\beta_{NBCT}$ using blockchain technology adopters as the treatment.

Expected productivity and gross margin of the blockchain technology adopters (observed)

$$E(Y_{iBCT}\ |BCT = 1) = X_{iBCT}\beta_{iBCT} + \sigma\mu_{iBCT}\lambda_{BCT}, \qquad (15)$$

Expected productivity and gross margin of the blockchain technology adopters if not adopting (Counterfactual)

$$E(Y_{iNBCT}\ |BCT = 1) = X_{iNBCT}\beta_{iNBCT} + \sigma\mu_{iNBCT}\lambda_{BCT}, \qquad (16)$$

Expected productivity and gross margin of the blockchain technology non-adopters (observed)

$$E(Y_{iNBCT}\ |BCT = 0) = X_{iNBCT}\beta_{iNBCT} + \sigma\mu_{iNBCT}\lambda_{NBCT,} \qquad (17)$$

Expected productivity and gross margin of the blockchain technology non-adopters if adopting (Counterfactual)

$$E(Y_{iBCT}\ |BCT = 0) = X_{iBCT}\beta_{iBCT} + \sigma\mu_{iBCT}\lambda_{NBCT}, \qquad (18)$$

where $\lambda_{BCT}$ and $\lambda_{NBCT}$ are inverse mills ratios for first and second regime equations respectively and it takes care of the selectivity bias, $X_{iBCT}$and $X_{iNBCT}$ are sets of explanatory variables, $\sigma\mu_{iBCT}$ and $\sigma\mu_{iNBCT}$ are covariance of the error terms.

Following Maddala (1983), the average treatment effect on the treated (ATT) was calculated by obtaining the difference between the observed productivity and gross margin of the BCT adopters and their counterfactual, while the average treatment effect on the untreated (ATU) were calculated by getting the difference between the observed productivity and gross margin of the BCT non-adopters and their counterfactual.

ATT calculations from equations 15 and 16

$$ATT = E(Y_{iBCT}\ |BCT = 1) - E(Y_{iNBCT}\ |BCT = 1), \qquad (19)$$

ATU calculations from equations 17 and 18

$$ATU = E(Y_{iNBCT}\ |BCT = 0) - E(Y_{iBCT}\ |BCT = 0) \qquad (20)$$

The variables that were used in the ESR model are derived from review of literature as described in Table 3.4.

**Table 3.4:** Variable for the Endogenous switching regression model

| Variables | Description | Measurement | Expected sign | Literature source |
|---|---|---|---|---|
| **Dependent variables** | | | | |
| Productivity | Barley yield per acre | Continuous (*Kgs*) | | |
| Gross margin | Total barley revenue minus total variable costs | Continuous (*USD*) | | |
| **Treatment variable** | | | | |
| BCT adoption | Blockchain technology adoption status | Binary (*1=adopters, 0=Non-adopters*) | +/_ | Schoeffel (2019); Costa *et al*., (2020) |
| **Independent Variables** | | | | |
| Main occupation | Main occupation of the respondent | Binary, (1=Farming 0=Non-farming) | + | Mottaleb (2018); Birthal *et al*., (2017) |
| Sex | Sex of the respondent | Binary (*1=male*, *0=otherwise*) | +/- | Mishra *et al*., (2017); FAO, (2023) |
| Seed_per_acre | Quantity of seeds planted per acre of barley farm | Continuous (Kgs) | + | Onyango *et al*., (2021); Goyal *et al*. (2022) |
| Fertil_per_acre | Quantity of fertilizers applied per acre of barley farm | Continuous (Kgs) | + | Onyango *et al*., (2021); Goyal *et al*., (2022) |
| Labour_per_acre | Hired labour per acre. | Continuous (Man/day/acre) | +/- | Alobid *et al*., (2022) |
| Barley_expereince | Number of years a farmer has spent practicing growing of barley | Continuous | +/- | Ainembabazi & Mugisha (2014) |

| | | | | |
|---|---|---|---|---|
| Age | Age of the respondent (Years) | Continuous | +/- | Okello, (2017) |
| Household_labour | Adult household members engaged in production | Continuous (Number of productive members) | + | Alobid *et al*., (2022) |
| Land_tenure | Form of land ownership arrangement of the farmer | Binary (1=Customary 0=Commercial) | +/- | Diendéré & Wadio, (2023) |
| Land_size | Total size of the land owned by the farmer | Continuous (Acres) | +/- | Temesgen & Aweke (2023); Emran *et al*., (2021) |
| BCTtraining | Whether a farmer received blockchain related training | Binary (1=Yes, 0=No) | + | AlShamsi *et al*., (2022); Silva *et al*., (2024) |
| Barly_farmsize | Size of land under barley production only | Continuous (*acres*) | + | Mugera *et al*., (2016) |
| Education level | Number of years in school | Continuous | + | Manning *et al*., (2022). |
| DistComp B buying centre | Distance to Company B buying centre | Continuous (Walking minutes) | +/- | Asfaw *et al*., (2018) |
| DistBarly_farm | Distance to the barley farm | Continuous (Walking minutes) | - | Alemu *et al*., (2017). |
| Grp_membership | Membership to farmer groups | Binary (1=Yes 0=No) | + | Nandhini *et al*., (2023) |
| Extension services | Number of agricultural extensions visits in a year | Continuous | + | Anang *et al*. (2020) |
| Netwk_connect | Mobile phone network stability | Binary (1=Stable, 0=Unstable) | + | Alammary *et al*., (2019) |
| Credit | Access to credit in the last 1 year | Binary (1=Yes 0=No) | + | Dong *et al*., (2024) |
| Nonbarlry_income | Non-barley farming income | Continuous (in USD) | + | Zhang *et al*., (2023b) |

### 3.6.5 Developing a suitable blockchain technology implementation framework based on Uganda's context

In the fourth objective, the aim was to identify and prioritize challenges affecting blockchain technology implementation so as to suggest solutions that would guide the development of an implementation framework based on Uganda's context, which may be adopted by other countries. Being a novel and disruptive technology, blockchain implementation is faced with several challenges, which may affect stakeholders in the barley value chain differently. Prioritizing is needed since addressing all of them at once or coming up with policies to address each challenge might be rather expensive given the scarcity of resources. Directing efforts at the most pressing challenge first may not only be economical but may also achieve success in implementation since efforts would be targeted at the most pressing challenge. Prioritizing was based on both quantitative and qualitative responses from 10 stakeholders in the barley value chain (2 farmer groups, 3 middlemen, 2 mid-level managers, and 3 field staff of Company B.

The data from group discussions was collected using semi-structured interviews. The group discussions and a semi-structured interview format were preferred over in-depth focus group discussions mainly because the questions were close ended in nature, desiring specific answers on prioritizing challenges and their solutions, and were explicitly designed to be asked by the researcher (Barrett & Twycross, 2018). The two group discussions' participants were selected from each district of Bukwo (Suam sub-county) and Kween (Kwosir sub-county). A number of 10 farmers per group was considered sufficient for a qualitative discussion since studies recommend 6-12 participants (Barrett & Twycross, 2018).  Notably, these participants had not taken part in the main survey of individual farmers. Furthermore, two group discussions were deemed sufficient to provide the required qualitative data, as highlighted by Guest *et al*. (2017), since all the participants were homogeneous.

There are a number of methodologies that could be used to achieve this objective. Firstly, after identifying the challenges, stakeholders would be asked to assign numerical weights on the challenges on a scale of 0-10. Secondly, stakeholders would otherwise assign subjective weights to the challenges, say from "most critical to least critical." Thirdly, conjoint analysis could be used since it follows the same system of allowing the participants to rate the challenge based on its attributes but includes an OLS regression. The first two may not be robust since the weights assigned may not necessarily be the actual weights of the challenge (Pyzdek & Keller, 2010). The third option treats all attributes of the challenges as quantitative and dummies (so as to avoid regarding the continuous nature of some attributes as scales of preference) which may not be the case in this study.

An alternative method suitable for this objective is the analytic hierarchy process (AHP), a Multi-criteria decision making (MCDM) model. This method is robust and it takes into account both the quantitative and qualitative data from the participants. The AHP combines both mathematics and psychology to prioritize criteria (challenge categories) in decision making. AHP was done through steps. Firstly, the goal was identified and in this case the goal was to prioritize critical challenges of blockchain technology implementation in order to suggest priority guided solutions. Secondly, challenges were identified and categorized, and sub-challenges in each category were identified depending on literature review (Mohammad Saif *et al*., 2022; Mohanta *et al.*, 2020; Queiroz & Fosso Wamba, 2019; Yadlapalli *et al*., 2022). Additionally, stakeholder consultations were carried out to further enhance the challenges identified from literature review. Accordingly, five categories and sub-categories are suggested as shown in Figure 3.4.

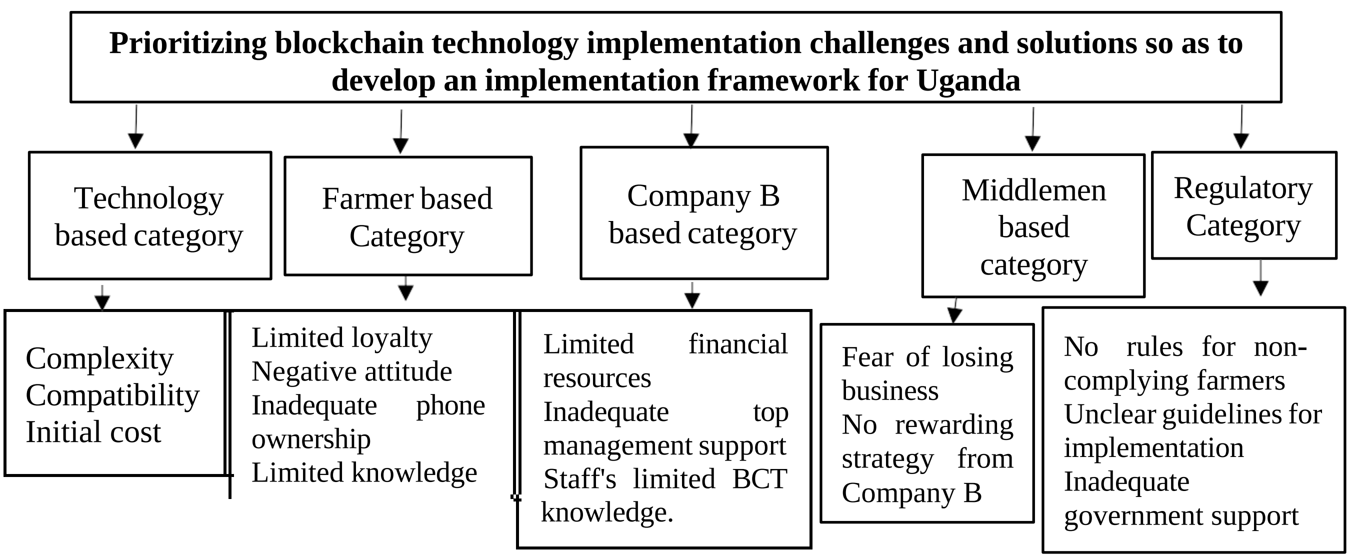


**Figure 3.4:** Conceptual model of blockchain implementation challenges in the barley value chain

In the third step, pair-wise comparison matrices for data collection were generated by comparing one challenge or sub-challenge with another one basing on stakeholder judgments (*ij*) of the criticality of the challenge. For a set of *n* challenge categories/sub-challenges in a matrix, the judgments needed are given as shown in equation 21a while equation 21b shows their reciprocals. The pair-wise matrices for the challenges and sub-challenges are shown in Appendix B. For this study, $n$=5, therefore, 10 judgements were needed, and their 10 reciprocals.

$$(n^2 - n)/2 \tag{21a}$$

$$a_{ij} = 1/a_{ij} \tag{21b}$$

whereby $a_{ij}$ is the aggregation of individual judgments.

The comparisons were based on 9-point scale of importance of the challenge category or sub-challenge. 1=Equal importance, 3=Moderate importance, 5=Strong importance, 7=Very strong importance, 9=Extreme importance. 2, 4, 6 and 8 are intermediate values. 1/2, 1/3,...1/9 are values for inverse comparisons (their reciprocals).

In the fourth stage, a normalized pair-wise matrix was generated from dividing the elements in the pair-wise matrix column by the sum of the column. Then, individual challenge/sub-challenge weights were computed by averaging all the elements in the normalized pair-wise matrix. A challenge with the highest weight was more critical than the next one, and therefore requires immediate attention than the next. In the final stage, consistency ratio (CR) was calculated to check whether the judgments by all the stakeholders are consistent or not. According to Saaty (1990), a CR $\leq 0.1$ is acceptable. Consistency ratio is obtained by dividing consistency index (CI) by random index (RI). CI is given by:

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{22a}$$

$$CR = \frac{CI}{RI} \tag{22b}$$

whereby $\lambda_{max}$ is obtained from the average of weighted sum value divided by individual challenge weight (the weighted sum value is obtained from multiplying the elements in non-normalized pair-wise matrix by the challenge weight, and summing the obtained values in the matrix rows), $n$ is the number of challenge categories, while random index is obtained from the random index table put forward by Saaty (1980). Since $n$=5 for this study, the RI was 1.12. In the final step, a blockchain technology implementation framework was developed basing on the prioritized challenges and suggested solutions, to aid decision making regarding future scalability.

# CHAPTER FOUR
# RESULTS PRESENTATION AND DISCUSSIONS

This chapter presents the findings and discussions on the impact of blockchain technology on the performance of barley farmers in the Sebei sub-region of eastern Uganda. The chapter is structured as follows: Section 4.1 provides descriptive statistics on farmer, farm, technological, and cost-benefit factors for both adopters and non-adopters of blockchain technology, along with the demographic characteristics of farmer groups and key informants. Section 4.2 examines results from the extended Technology Acceptance Model and social norm analysis to determine farmers' intentions to adopt blockchain. Section 4.3 discusses findings from the Double Hurdle Model estimation, while Section 4.4 details the results from the Endogenous Switching Regression Model on the effects of blockchain technology on farm productivity and gross margins. Finally, Section 4.5 presents priority challenges impeding blockchain implementation using the Analytical Hierarchy Process, and their priority solutions, and concludes with a proposed framework for successful blockchain implementation in Uganda's barley value chain context.

## 4.1 Descriptive statistics

### 4.1.1 Farmer related socioeconomic characteristics

The study collected data on the socioeconomic characteristics of the sampled farmers, and Table 4.1 presents the overall and mean differences between blockchain technology adopters and non-adopters. The average age of all sampled farmers was 42.08 years. Adopters had a slightly higher mean age (42.6 years) than non-adopters (41.6 years), though the difference was not statistically significant. These similar mean ages suggest that barley farmers were in their productive years. Age influences decision-making, with older farmers often making quicker and more informed choices, while middle-aged farmers, like those in this study, tend to balance experience and openness to new technologies. The slightly older adopters may have greater access to information, decision-making authority, or financial stability, enabling them to adopt innovations like blockchain. Yokamo (2020) similarly observed that middle-aged farmers are more likely to embrace modern technologies to improve farm performance.

Results on education indicate that the average years of schooling for blockchain technology adopters was 9.9, slightly higher than the 9.5 years for non-adopters. This indicates that most farmers had reached at least Senior Two in Uganda's education system, equipping them to use blockchain technology effectively. Education plays a critical role in adopting agricultural technologies, and the slightly higher education levels among adopters suggest that more educated farmers are more likely to embrace such innovations, as also noted by Gao *et al*. (2018). Overall, the sampled farmers had an average of nine years of schooling, equivalent to Senior Two, reflecting a considerable level of secondary education. In terms of experience in barley farming experience, blockchain technology adopters had spent an average of 8.7 years in the enterprise, compared to 7.4 years for non-adopters. This difference was statistically significant at the 1% level, suggesting that more experienced farmers are more inclined to adopt technologies like blockchain to enhance their performance as suggested by Kernecker *et al*. (2020).

Concerning household size, the average size of households for blockchain technology adopters was 8 persons, compared to 7 for non-adopters. Though this difference was not statistically significant, it suggests that adopting households were slightly larger. According to the Uganda National Household Survey 2019/2020 by UBOS, rural households typically range from 5 to 7 persons, making the adopters' households notably larger. Larger household sizes in African farming communities are often associated with access to cheaper labor (Shilomboleni *et al*., 2024) but can also strain resources, such as income, which might otherwise be invested in farming and adopting new technologies (Mutungi *et al*., 2023). On the size of land owned, the blockchain adopting households owned bigger mean land sizes (3.3 acres) than non-adopting households (2.9 acres) and this mean difference was statistically significant at 5% level. Land is a key resource in farming (Noack & Larsen, 2019) and ownership is a symbol of stability, social status, can be used as security to acquire credit resources and investment in sustainable practices and technologies.

Considering incomes from non-barley farming activities, the overall mean income from non-barley farming activities was USD 311.57. The blockchain adopting households had a higher mean income from non-barley farming activities of USD 331.82 compared to USD 291.40 for non-adopting households. This significant difference at the 5% level may suggest better financial stability and diversification among adopters. This could suggest that households with higher incomes from other farming activities are more likely to adopt blockchain technology, as they may have greater financial flexibility to invest in new innovations and absorb associated risks. Additionally, higher incomes from diversified activities may reflect better access to resources, market opportunities, and knowledge, which could facilitate the adoption of blockchain technology. This aligns with the idea that financial capacity plays a significant role in technology adoption, as households with more stable income sources are often better positioned to explore and implement modern agricultural practices (Geng *et al*., 2024).

Blockchain technology adopting farmers had an average group membership period of 3 months, which was significantly higher than the 1.8 months for non-adopters. This average difference may be explained by the role of farmer groups in facilitating social influence and peer learning. Through group interactions, blockchain adopters were likely able to gain insights and share experiences, which helped reduce uncertainty and build confidence in adopting blockchain technology (Manda *et al*., 2020). On average, both the BCT adopting and non-adopting farmers received agricultural extension training the same number of times (2.4) in a year.

**Table 4.1**: Farmer socio-economic characteristics (Continuous variables)

| | BCT adopters (N=245) | | BCT non-adopters(N=246) | | Overall sample (N=491) | | |
|---|---|---|---|---|---|---|---|
| Variable | Mean | Std.dev | Mean | Std.dev | Mean | Std.dev | *t*-test |
| Age | 42.58 | 11.00 | 41.59 | 11.37 | 42.08 | 11.19 | 0.980 |
| Schooling years | 9.91 | 3.99 | 9.54 | 3.66 | 9.73 | 3.83 | 1.059 |
| Barley farming experience (years) | 8.67 | 3.66 | 7.41 | 2.89 | 8.03 | 3.36 | 4.227*** |
| Household size | 7.56 | 2.97 | 7.44 | 3.10 | 7.50 | 3.03 | 0.439 |
| Size of land owned (acres) | 3.29 | 2.22 | 2.91 | 1.90 | 3.10 | 2.07 | 2.059** |
| Non-barley income (USD) | 331.82 | 203.82 | 291.40 | 187.80 | 311.57 | 187.80 | 2.396 ** |
| Group membership (period in months) | 3.07 | 6.33 | 1.86 | 4.36 | 2.46 | 5.45 | 2.481** |
| Extension frequency | 2.47 | 1.28 | 2.44 | 1.40 | 2.45 | 1.34 | 0.318 |

Note: *, ** and *** denotes = significant at 10%, 5% and 1% level, respectively

**Farmer-socio-economic characteristics (Categorical variables):** The study results found significantly higher percentages of male headed households than female headed ones across the blockchain adopting (87.4%) and non-adopting farmers (92.2%). The small percentage of female headed households (adopters =12.7% and non-adopters=7.7%) supports the popular literature that male headed household stand a better chance of accessing information and production resources which could enhance use of agricultural technologies like blockchain (Marter-Kenyon *et al*., 2022). This is largely due to cultural norms that prioritize men's roles in farming, making it easier for male-headed households to receive extension services, access credit, and participate in farming networks. Majority of the farmers sampled were married (95.1% and 96.8%, BCT adopters and non-adopters respectively) in contrast to 4.9% blockchain adopters and 3.3% non-adopters who were single. Marital status influences decision making and household resource allocation which are vital considerations for agricultural technologies adoption and use (Businge *et al*., 2024).

The main occupation of the sampled farmers was farming (including barley farming) as opposed to other non-farming economic activities such as trade in agricultural and non-agricultural products, salaried employment, and pensions. Among the blockchain technology adopters, 95.9% were engaged mainly in farming compared to 4.8% that engaged mainly in non-farming activities. Equally, 92.7% of blockchain non-adopters mainly practiced farming in contrast to 7.3% that were engaged in non-farming activities. This finding upholds the dominance and importance of smallholder farmers in African rural communities (Kamara *et al*., 2019), thus the need for them to embrace modern agricultural technologies like blockchain in various value chains to improve farm performance. Concerning ownership of mobile phones, 97.1% blockchain adopters and 95.1% BCT non-adopters owned mobile phones in contrast to 2.9% and 4.9% blockchain adopters and non-adopters respectively who did not own mobile phones. Though most farmers had key pad phones (76.7% blockchain adopters and 76.8% non-adopters) instead of sensory ones (20.4% for blockchain adopters and 18.3% for blockchain non-adopters), the mere possession signifies the usefulness of mobile phones in accessing and using agricultural information and technologies like blockchain (Krell *et al*., 2021). The flexibility of the BanQu blockchain technology app enabled it to be installed on both sensory and keypad mobile phones, ensuring greater accessibility and inclusion for most farmers.

In relation to power connectivity, a very small percentage of farmers (1.2% blockchain adopters and 1.6% non-adopters) were connected to the national grid (Hydro Electricity power, HEP). The majority of farmers relied on solar power as their primary energy source, with 91.8% of adopters and 91.9% of non-adopters using solar alternatives. In contrast, only 0.41% of farmers used rechargeable batteries. Comparably, 6.5% of blockchain technology adopters and non-adopters had no connection to any power source at all. Farmers relied on these power alternatives to charge their mobile phones, which served as the primary platform for accessing and using the technology. The finding that only a small percentage of farmers were connected to the national grid aligns with Peters *et al*. (2019), who reported that nearly 1 billion households in developing countries lack access to grid electricity (HEP). The reliability on solar power by majority households presents challenges of power inconsistencies to serve the household needs of lighting and mobile phone charging to support blockchain technology use.

In the same line, network stability is key for farmers in relation to adoption of agricultural technologies like blockchain which necessitates use of mobile phones. As such, 51.4% blockchain adopters and 67.1% non-adopters reported having stable network connectivity throughout the year, against 48.6% blockchain adopters and 32.9% non-adopters that reported otherwise. This mean difference was statistically significant at 1% level of significance. The relatively stable network facilitates regular exchange of information across the actors in the barley value chain enabled through blockchain technology (MacPherson *et al*., 2022).

Regarding access to credit by farmers, the results were interestingly lower for blockchain adopters (29.4%) compared to non-adopters (52%). This suggests that non-adopting farmers relied more on credit to finance their barley value chain operations than adopting farmers. Moreover, this difference was statistically significant at the 1% level. The probable explanation for this contrast is that adopting blockchain initially was supposed to provide adopting farmers with access to inputs at no cost, with payment due upon delivery of barley to the company buying centres. Thus, this finding supports the usefulness of blockchain in reducing transactional costs of barley farmers (Ahluwalia *et al*., 2020).

The results on land tenure showed that 99.18% of blockchain adopters and 93.90% of non-adopters owned land under customary tenure, while only 0.82% of adopters and 6.10% of non-adopters had non-customary (commercial) tenure. The mean difference in land tenure between the two groups was statistically significant at the 1% level. These findings suggest that the majority of barley farmers in the study area, regardless of their blockchain adoption status, operated under customary land tenure. However, a significantly higher proportion of non-adopters had access to non-customary land tenure compared to adopters. This indicates that farmers with non-customary land tenure were more likely to adopt blockchain, while those with customary land tenure were less likely to do so. This finding aligns with the argument that land tenure security plays a crucial role in the willingness of farmers to invest in modern agricultural technologies (Lawry *et al*., 2017).

**Table 4.2:** Farmer-based socio-economic characteristics (Categorical variables)

| Categorical Variables | BCT adopters (N=245) | BCT non-adopters (N=246) | Overall sample (N=491) | $\chi^2$ |
|---|---|---|---|---|
| **Extension services (%)** | | | | 0.922 |
| Yes | 80.00 | 76.42 | 78.21 | |
| No | 20.00 | 23.58 | 21.79 | |
| **Sex (%)** | | | | 3.261* |
| Male | 87.35 | 92.28 | 89.82 | |
| Female | 12.65 | 7.72 | 10.18 | |
| **Marital status (%)** | | | | 0.851 |
| Married | 95.10 | 96.75 | 95.93 | |
| Single/divorced/widowed | 4.90 | 3.25 | 4.07 | |
| **Main occupation** | | | | 2.389 |
| Farming (barley inclusive) | 95.92 | 92.68 | 94.30 | |
| Non-farming (others) | 4.8 | 7.32 | 5.70 | |
| **Phone ownership (%)** | | | | 1.348 |
| Yes (owned phone) | 97.14 | 95.12 | 96.13 | |
| No (did not own phone) | 2.86 | 4.88 | 3.87 | |
| **Phone type (%)** | | | | 1.579 |
| Sensory | 20.41 | 18.29 | 19.35 | |
| Keypad | 76.73 | 76.83 | 76.78 | |
| **Power connectivity (%)** | | | | 1.143 |
| Grid (Hydroelectric power) | 1.22 | 1.63 | 1.43 | |
| Solar | 91.84 | 91.87 | 91.85 | |
| Rechargeable batteries | 0.41 | 0.00 | 0.20 | |
| Not connected at all | 6.53 | 6.50 | 6.52 | |
| **Network stability (%)** | | | | 12.445 *** |
| Stable | 51.43 | 67.07 | 59.27 | |

| | | | | |
|---|---|---|---|---|
| Unstable | 48.57 | 32.93 | 36.86 | |
| **Credit access (%)** | | | | 26.073 |
| Yes | 29.39 | 52.03 | 40.73 | *** |
| No | 70.61 | 47.97 | 59.27 | |
| **Land tenure (%)** | | | | 10.243 |
| Customary tenure (=1) | 99.18 | 93.90 | 96.54 | *** |
| Non-customary (=0) | 0.82 | 6.10 | 3.46 | |

Note: *, ** and *** denotes = significant at 10%, 5% and 1% level, respectively

### 4.1.2 Farm related characteristics

The study collected data on barley farm-related characteristics, and the results are presented in Table 4.3. From the results, both blockchain adopting and non-adopting households were closer to their barley farms with average time taken to walk from the house to the farm being 5.2 minutes and 4.6 respectively. The location of households closer to the barley farms was deemed advantageous for proper supervision, frequent monitoring, and management of the farm for improved performance (Li *et al*., 2022). Regarding the distance to Company B buying centres, blockchain-adopting households were located closer, with an average distance of 7.2 km, compared to non-adopting households, which were farther away at an average of 8.4 km. This difference was statistically significant at the 1% level. The proximity of adopting farmers to Company B buying centres may explain their higher adoption rates, as it allowed them easier access to services such as registration, input acquisition, and produce delivery. This finding aligns with Ahmed *et al*. (2017), who reported that farmers located closer to input sources and market centres are more likely to adopt agricultural technologies.

The results on proximity to trading centres revealed that blockchain non-adopting households were closer, with an average walking time of 9.3 minutes compared to 11.1 minutes for adopters. This mean difference was statistically significant at the 10% level. The shorter distance suggests that non-adopters relied more on trading centres to purchase farming inputs such as seeds and agrochemicals, whereas the adopters primarily obtained their inputs from Company B buying centres. Proximity to trading centres likely reduced transportation costs and travel time, allowing non-adopters to access inputs more frequently and at lower costs (Rutsaert *et al*., 2021).

Regarding the size of barley farms, both blockchain adopters and non-adopters farmed an average of 1.2 acres, which made the difference in farm sizes statistically insignificant. This indicates that all the sampled farmers were cultivating barley on relatively small farms. The small size of these farms could be attributed to factors such as limited production resources and customary tenure systems, which promote land fragmentation. To enhance productivity and overall performance on such small-scale farms, the adoption of modern technologies like blockchain is essential. These small sizes of barley farms align with the findings of Giller *et al*. (2021), who noted that most smallholder agriculture in sub-Saharan Africa is conducted on considerably small farms.

**Table 4.3:** Farm related characteristics

| | BCT adopters (N=245) | | BCT non-adopters(N=246) | | Overall sample (N=491) | | |
|---|---|---|---|---|---|---|---|
| Continuous Variable | Mean | Std.dev | Mean | Std.dev | Mean | Std.dev | *t*-test |
| Household distance to barley farm (mins) | 5.16 | 6.17 | 4.61 | 6.20 | 4.88 | 6.19 | 0.991 |
| Distance to buying centre (KM) | 7.19 | 4.00 | 8.39 | 3.85 | 7.79 | 3.97 | 3.408*** |
| Household distance to trade centre (mins) | 11.12 | 11.55 | 9.31 | 9.61 | 10.21 | 10.65 | 1.896* |
| Barley farm size (acres) | 1.25 | 0.68 | 1.22 | 0.81 | 1.25 | 0.78 | 0.128 |

Note: *, ** and *** denote = significant at 10%, 5% and 1% level, respectively

### 4.1.3 Cost-benefit related factors

The cost benefit related factors are presented in Table 4.4**.** From the results, 76.7% of adopting farmers and 95.9% of non-adopting farmers reported to have received blockchain related training before and after enrolment on the BanQu blockchain technology app. The mean percentage differences between the farmers that received training and those that did not was statistically significant at 1% level. This finding implies that blockchain related training was availed to all farmer prior to enrolment, thus subsequent decision to adopt the technology was purely voluntary. It could also imply that even after enrolment, blockchain related training was still provided to every farmer that wished to attend irrespective of their adoption status. This emphasises the usefulness of blockchain tailored training in the implementation process (Leung *et al*., 2024).

Blockchain technology adopters sourced most inputs from Company B (88.6%) and sold outputs exclusively back to it (100%), while non-adopters primarily used other suppliers like agro-input shops, middlemen, and market places (73.6%) and sold largely to middlemen (52.3%). The mean differences in input sources and output buyers between adopters and non-adopters were statistically significant at 1% level. This indicates that blockchain facilitated smoother transactions with Company B through transparent pricing and secured market access, which likely contributed to higher adoption rates. The findings align with those of Gandhi Maniam *et al*. (2024) who reported that blockchain is a transformative tool for smallholder farmers who benefit from increased transparency, efficiency, and market access.

In addition, the average costs of blockchain related training received before and after farmer enrolment for both adopters and non-adopters were USD 0.33 and USD 0.0033. This difference was statistically significant at 1% level, implying that the adopting farmers incurred more costs on training than the non-adopting farmers. This could be attributed to the adopters realizing the tangible benefits of blockchain technology to the barley value chain activities and thus were willing to spend on the trainings as opposed to their non-adopter counterparts. This finding is similar to that of Vern *et al.* (2024) who found that despite the high cost of agricultural training, farmers are willing to pay for it especially if it benefits their farming ventures.

Likewise, the costs of production and marketing of barley output were higher for blockchain adopters compared to non-adopters. Specifically, the average cost of production per acre was USD 207.10 for adopters and USD 184.10 for non-adopters. Similarly, marketing costs per acre were higher for adopters (USD 22.87) than for non-adopters (USD 18.85). These differences in production and marketing costs were statistically significant at the 10% and 5% levels, respectively. These discrepancies are likely due to variations in output levels, with blockchain adopters likely experiencing higher yields due to the benefits of blockchain, such as improved access to inputs, better pricing, and valuable information. As a result, adopters incurred higher production costs, including those for seeds, fertilizers, and marketing-related expenses like transportation, compared to non-adopters (Liu *et al*., 2022).

**Table 4.4:** Cost-benefit related factors

| Categorical variables | BCT adopters (N=245) | | BCT non-Adopters (N=246) | | Overall sample (N=491) | | $\chi^2$ |
|---|---|---|---|---|---|---|---|
| **BCT related training (%)** | | | | | | | 38.402 |
| Yes | 76.73 | | 95.93 | | 86.35 | | *** |
| No | 23.27 | | 4.07 | | 13.65 | | |
| **Main input source (%)** | | | | | | | 193.933 |
| Company B stores | 88.6 | | 26.4 | | 57.43 | | *** |
| Other sources | 11.4 | | 73.6 | | 42.57 | | |
| **Main output buyer (%)** | | | | | | | 174.258 |
| Company B | 100 | | 47.6 | | 47.6 | | *** |
| Middlemen | 0.0 | | 52.4 | | 52.4 | | |
| Continuous variable | BCT adopters (N=245) | | BCT non-adopters (N=246) | | Overall sample (N=491) | | |
| | Mean | Std.dev | Mean | Std.dev | Mean | Std.dev | *t*-test |
| BCT training cost (USD) | 0.33 | 1.19 | 0.0033 | 0.039 | 0.17 | 0.86 | 4.281*** |
| Marketing costs (USD/acre) | 22.87 | 19.29 | 18.85 | 27.78 | 20.86 | 23.98 | 1.859* |
| Production costs (USD/acre) | 207.10 | 112.55 | 184.10 | 131.68 | 195.58 | 122.93 | 2.079** |

Note: *, ** and *** denotes = significant at 10%, 5% and 1% level, respectively

1 USD =Ugx 3,682/= as of 2025

### 4.1.4 Descriptive statistics for farmer group discussion participants and Key informants

The farmer group discussions and key informant interviews provided data on identifying and prioritizing blockchain technology implementation challenges and solutions, which could not be accurately captured through the main survey of individual farmers. The semi-structured interviews in the two group discussions included 11 participants from Bukwo (Suam sub-county) and 10 from Kween (Kwosir sub-county). In Bukwo, 63.6% of participants were male, while in Kween, this figure was 70%, indicating a predominance of male participation in community meetings and programs in these rural areas. This gender imbalance reflects traditional norms that often limit women's participation in such forums, as many females were occupied with other responsibilities and opted not to attend. Consequently, men filled their places. Obayelu *et al*. (2019) observed similar male dominance in rural community engagement, noting that cultural norms frequently restrict women's involvement. The participants' extensive experience of over seven years in barley farming provided a strong foundation for discussing challenges in the barley value chain, particularly regarding BCT implementation.

**Table 4.5:** Demographic characteristics of group discussions participants

| District | Number of participants | Composition based on sex | Homogeneity |
|---|---|---|---|
| Bukwo | 11 | 7men (63.6%) 4 women (36.4%) | All were adult barley farmers with over 7 years of experience, residing in the same area and sharing a similar cultural background. Barley growing was their major economic activity |
| Kween | 10 | 7 men (70%) 3women (30%) | All were adult barley farmers with over 7 years of experience, residing in the same area and sharing a similar cultural background. Barley growing was their major economic activity |

As indicated in Table 4.5 the key informant interviews involved participants aged 18 to 50, suggesting they were in a productive stage of life, well-positioned to actively engage in the value chain and facilitate the adoption of blockchain technology (Wang *et al*. 2021). Except for MM 3, who was widowed, all key informants were married. The staff from Company B, including both field staff and mid-level managers, had achieved tertiary education, holding diplomas or bachelor's degrees. This educational background implies sufficient literacy to grasp the complexities of blockchain, concurring with findings by Chang *et al*. (2022) that emphasize the need for knowledgeable technical staff to support blockchain implementation.

**Table 4.6:** Demographic characteristics of key informants

| Participant (pseudo name) | Sex | Age | Marital status | Education level | Role in the value chain |
|---|---|---|---|---|---|
| MM 1 | Male | 40 | Married | Secondary | Middleman |
| MM 2 | Male | 50 | Married | Primary | Middleman |
| MM 3 | Female | 45 | Widowed | Primary | Middleman |
| FS 1 | Female | 32 | Married | Bachelors | Field staff of Company B |
| FS 2 | Female | 30 | Married | Bachelors | Field staff of Company B |
| FS 3 | Female | 35 | Married | Bachelors | Field staff of Company B |
| MLM 1 | Male | 38 | Married | Bachelors | Mid-level manager of Company B |
| MLM 2 | Male | 48 | Married | Diploma | Mid-level manager of Company B |

## 4.2 Farmers' behavioural intentions to accept blockchain technology

This section explores the factors influencing farmers' intentions to accept blockchain technology, focusing on their behavioural and psychological drivers. It examines the key determinants of acceptance, providing insights into the motivations behind farmers' willingness to adopt blockchain technology.

### 4.2.1 Model fit assessment of the second extension of the technology acceptance model as estimated by partial least squares structural equation modelling

This subsection evaluates the goodness of fit for the TAM2 using PLS-SEM. It provides an assessment of how well the model fits the data, offering a basis for understanding the relationship between the identified constructs and farmers' behavioural intentions to adopt blockchain technology. The results of the model fit measures are presented in Table 4.7. The commonly used measure is the standard root mean square residual (SRMR) value which displays the average size of differences between the correlations that are observed and those that are implied by the model. As such, it offers an evaluation of the residuals of the model. The threshold value of SRMR is less or equal to 0.08 (Hair *et al*., 2021; Henseler *et al*., 2016). From the results, the SRMR value obtained was 0.068 (for the saturated model) and 0.073 (for the estimated model) which is above the 0.08 threshold, thus the model fitted well the data.

**Table 4.7**: Test results of the model fit

| Measurement criteria | Saturated model | Estimated model |
|---|---|---|
| SRMR | 0.068 | 0.073 |
| d_ULS | 5.047 | 5.753 |
| d_G | 1.716 | 1.789 |
| Chi-square | 2220.853 | 2275.93 |
| NFI | 0.62 | 0.61 |

*Note:* SRMR denotes Standardized Root Mean Square Residual; d_ULS denotes Squared Euclidean Distance; d_G= Geodesic Distance (both d_ULS and d_G are measures of exact fit), and NFI=Normed Fit Index

### 4.2.2 Results of the measurement model assessment

This sub-section describes the reliability and validity tests which are used to report the quality of the reflective measurement model. These tests include the outer loadings, reliability and validity, and collinearity statistics (Variance inflation factor, VIF), some of which are presented in Figure 4.1.

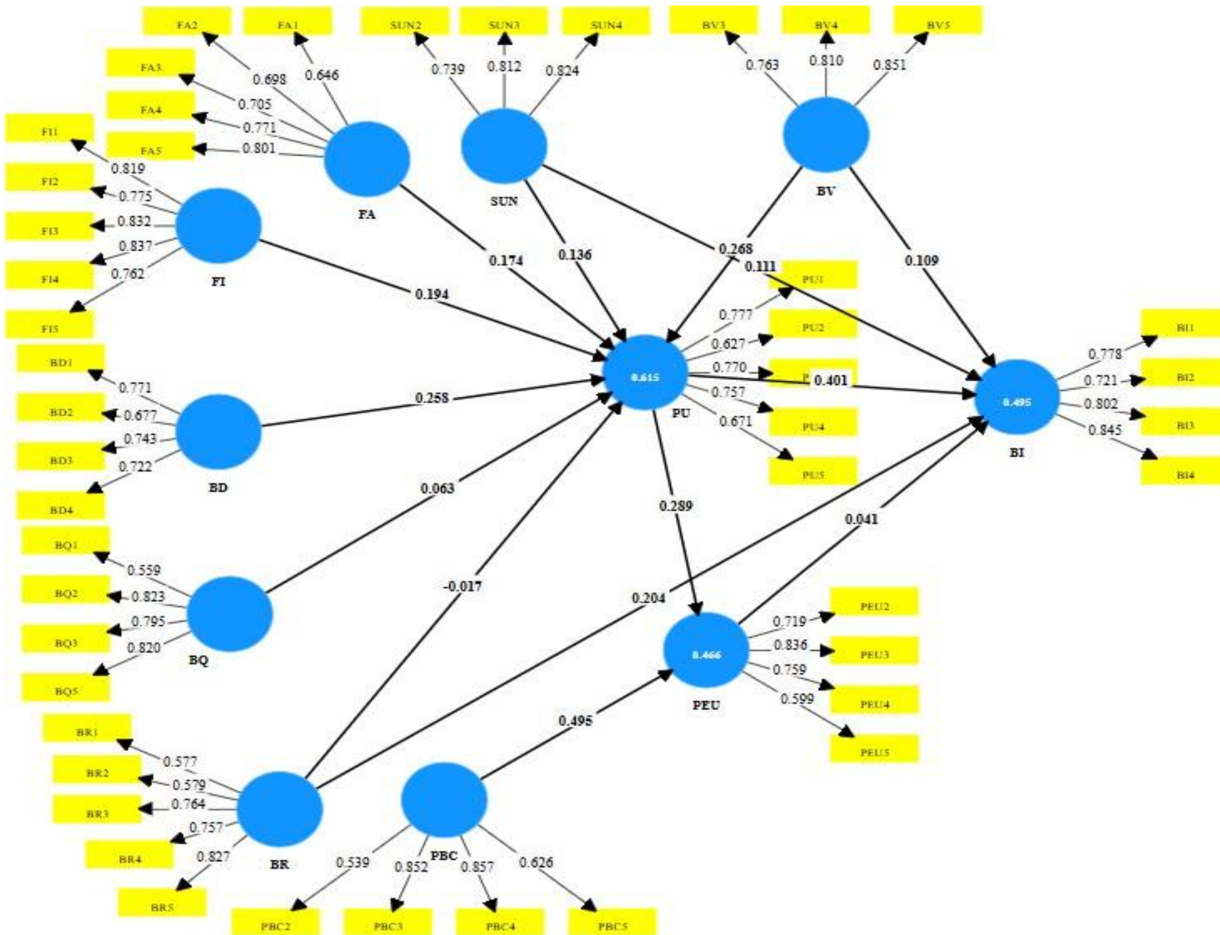


**Figure 4.1**: TAM2 measurement model

**Outer loadings:** Outer loadings measure the degree of each item's correlation with the specified principal component in the correlation matrix. The values for the outer loadings can range from -1.0 to 1.0, with higher absolute values indicating a higher correlation of the item with the underlying construct. Most studies recommend indicator loading values above 0.70. Initially, some indicators on different constructs had loadings lower than 0.70 and these were eliminated one by one to remain with those indicators that had a higher correlation with the underlying constructs. However, care was taken while doing the elimination so as not to eliminate indicators which had reducing effect on the internal consistency reliability and convergent validity even when their values were below 0.70. Hair *et al*. (2017) recommends indicator loading values of not less than 0.50 for most social science-based research, and as such all the construct indicators in this study's measurement model had outer loading values above 0.50 as presented in Figure 4.1 and Table 4.8.

**Table 4.8:** Measurement model outer loadings

| | BD | BI | BQ | BR | BV | FA | FI | PBC | PEU | PU | SUN |
|---|---|---|---|---|---|---|---|---|---|---|---|
| BD1 | 0.771 | | | | | | | | | | |
| BD2 | 0.677 | | | | | | | | | | |
| BD3 | 0.743 | | | | | | | | | | |
| BD4 | 0.722 | | | | | | | | | | |
| BI1 | | 0.778 | | | | | | | | | |
| BI2 | | 0.721 | | | | | | | | | |
| BI3 | | 0.802 | | | | | | | | | |
| BI4 | | 0.845 | | | | | | | | | |
| BQ1 | | | 0.559 | | | | | | | | |
| BQ2 | | | 0.823 | | | | | | | | |
| BQ3 | | | 0.795 | | | | | | | | |
| BQ5 | | | 0.820 | | | | | | | | |
| BR1 | | | | 0.577 | | | | | | | |
| BR2 | | | | 0.579 | | | | | | | |
| BR3 | | | | 0.764 | | | | | | | |
| BR4 | | | | 0.757 | | | | | | | |
| BR5 | | | | 0.827 | | | | | | | |
| BV3 | | | | | 0.763 | | | | | | |
| BV4 | | | | | 0.810 | | | | | | |
| BV5 | | | | | 0.851 | | | | | | |
| FA1 | | | | | | 0.646 | | | | | |
| FA2 | | | | | | 0.698 | | | | | |
| FA3 | | | | | | 0.705 | | | | | |
| FA4 | | | | | | 0.771 | | | | | |
| FA5 | | | | | | 0.801 | | | | | |
| FI1 | | | | | | | 0.819 | | | | |
| FI2 | | | | | | | 0.775 | | | | |
| FI3 | | | | | | | 0.832 | | | | |
| FI4 | | | | | | | 0.837 | | | | |

| | | | | | |
|---|---|---|---|---|---|
| FI5 | 0.762 | | | | |
| PBC2 | | 0.539 | | | |
| PBC3 | | 0.852 | | | |
| PBC4 | | 0.857 | | | |
| PBC5 | | 0.626 | | | |
| PEU2 | | | 0.719 | | |
| PEU3 | | | 0.836 | | |
| PEU4 | | | 0.759 | | |
| PEU5 | | | 0.599 | | |
| PU1 | | | | 0.777 | |
| PU2 | | | | 0.627 | |
| PU3 | | | | 0.770 | |
| PU4 | | | | 0.757 | |
| PU5 | | | | 0.671 | |
| SUN2 | | | | | 0.739 |
| SUN3 | | | | | 0.812 |
| SUN4 | | | | | 0.824 |

**Construct reliability:** Construct reliability measures how consistently the findings hold true across constructs. When the same respondent's data is recollected under comparable circumstances, and similar outcomes are obtained, then the construct's measure is considered reliable. This study adopted three measures of assessing reliability namely Cronbach’s alpha, rho_a, and Jöreskog’s (1971) composite reliability (rho_c). Cronbach’s alpha is considered traditional and conservative approach as it assumes that all the indicator loadings are the same in the population, commonly known as *tau-equivalence*. Composite reliability (rho_c) on the other hand is considered liberal, thus the truest reliability was given by rho_a whose values depict the values between Cronbach’s alpha and Composite reliability.

The values of composite reliability should be over a threshold level of 0.70 for internal consistency reliability to be established in most scientific research. The higher the values the higher the reliability however, rho_c values higher than 0.95 indicate that indicators are redundant which reduces their reliability and consequent validity (Hair *et al*., 2021). Even though rho_c values between 0.60 and 0.70 are acceptable in exploratory research, results in Table 4.9 indicate that all the values of Cronbach’s alpha, rho_ a, and rho_c were all well above 0.70 but below 0.95 which means that internal consistency reliability was established across all the constructs used in this study.

**Table 4.9:** Construct reliability

| | Cronbach's alpha | Composite reliability (rho_a) | Composite reliability (rho_c) |
|---|---|---|---|
| BD | 0.706 | 0.705 | 0.819 |
| BI | 0.795 | 0.803 | 0.867 |
| BQ | 0.741 | 0.756 | 0.840 |
| BR | 0.744 | 0.767 | 0.831 |
| BV | 0.737 | 0.750 | 0.850 |
| FA | 0.775 | 0.786 | 0.847 |
| FI | 0.864 | 0.866 | 0.902 |
| PBC | 0.717 | 0.787 | 0.817 |
| PEU | 0.712 | 0.747 | 0.821 |
| PU | 0.770 | 0.779 | 0.845 |
| SUN | 0.704 | 0.713 | 0.835 |

**Construct validity:** Construct validity measures the accuracy of the data used to measure the constructs. It helps to establish whether the constructs measure what was intended to be measured. Construct validity was established statistically through convergent and discriminant validity assessments of the measurement model.

**Convergent Validity (Average variance extracted, AVE):** Convergent validity establishes how much variance is extracted as the indicators converge to measure an underlying construct. This validity is given by the average variance extracted (AVE). When the AVE value is greater than 0.50, then convergent validity is established, and it means that all the indicators are coming together to represent a given construct (Hair *et al.*, 2017). This study results in Table 4.10 indicate that the values of AVE for all the constructs were above 0.50.

**Table 4.10:** Convergent validity (AVE)

| Construct | Average variance extracted (AVE) |
|---|---|
| BD | 0.531 |

| | |
|---|---|
| BI | 0.620 |
| BQ | 0.573 |
| BR | 0.502 |
| BV | 0.655 |
| FA | 0.527 |
| FI | 0.649 |
| PBC | 0.536 |
| PEU | 0.538 |
| PU | 0.523 |
| SUN | 0.628 |

**Discriminant Validity:** Discriminant validity is a measure of distinctiveness among the constructs. It assesses whether or not the construct has its own individual identity. Given that PLS-SEM involves a variety of constructs such as the ones involved in the second extension of TAM for this study's case, it is important to establish that each construct has its own identity to eliminate issues of collinearity among constructs. Discriminant validity was assessed using three methods namely Fornell and Larcker Criterion (1981), Heterotrait-monotrait ratio (HTMT ratio), and cross loadings.

**Fornell and Larcker-Criterion (1981):** This measure was put forward by Fornell and Larcker (1981), who proposed that the squared variance within each construct, or the square root of AVE, should be compared to the inter-construct correlation of that construct and all other constructs under measurement in the model as a measure of shared variance between constructs. The shared variance between all model constructs should not exceed their AVEs. Therefore, discriminant validity is established by a larger square root of AVE of a construct relative to its association with all other constructs in the study. This measure's condition was achieved by the results since all the square roots of AVEs of each construct (indicated by the diagonal values) were larger than a construct's association with all other measured constructs in the study, as presented in Table 4.11.

**Table 4.11:** Fornell and Larcker criterion

| | BD | BI | BQ | BR | BV | FA | FI | PBC | PEU | PU | SUN |
|---|---|---|---|---|---|---|---|---|---|---|---|
| BD | **0.729** | | | | | | | | | | |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| BI | 0.573 | **0.787** | | | | | | | | | |
| BQ | 0.302 | 0.301 | **0.757** | | | | | | | | |
| BR | 0.541 | 0.542 | 0.379 | **0.708** | | | | | | | |
| BV | 0.416 | 0.501 | 0.211 | 0.483 | **0.809** | | | | | | |
| FA | 0.601 | 0.646 | 0.330 | 0.571 | 0.443 | **0.726** | | | | | |
| FI | 0.479 | 0.588 | 0.196 | 0.411 | 0.395 | 0.566 | **0.806** | | | | |
| PBC | 0.458 | 0.513 | 0.074 | 0.500 | 0.496 | 0.466 | 0.356 | **0.732** | | | |
| PEU | 0.404 | 0.473 | 0.164 | 0.525 | 0.504 | 0.455 | 0.352 | 0.634 | **0.733** | | |
| PU | 0.627 | 0.645 | 0.328 | 0.521 | 0.582 | 0.633 | 0.569 | 0.482 | 0.528 | **0.723** | |
| SUN | 0.372 | 0.463 | 0.302 | 0.489 | 0.355 | 0.469 | 0.309 | 0.487 | 0.526 | 0.479 | **0.793** |

**Heterotrait-monotrait (HTMT) ratio:** The Heterotrait-Monotrait (HTMT) ratio of correlations is a more effective method for assessing discriminant validity than the Fornell-Larcker Criterion (1981), as proposed by Henseler *et al*. (2015). The HTMT ratio is calculated by dividing the average correlations between indicators of different constructs (heterotrait-heteromethod correlations) by the geometric mean of the correlations among indicators of the same construct (monotrait-heteromethod correlations). According to Henseler *et al*. (2015), the recommended threshold for HTMT is 0.85 for constructs that are conceptually similar and 0.90 for constructs that are more distinct. This study's findings achieved the HTMT value thresholds as all the values are less or equal to 0.90, as presented in Table 4.12.

**Table 4.12:** Heterotrait-monotrait (HTMT) ratio results

| | BD | BI | BQ | BR | BV | FA | FI | PBC | PEU | PU |
|---|---|---|---|---|---|---|---|---|---|---|
| BD | | | | | | | | | | |
| BI | 0.758 | | | | | | | | | |
| BQ | 0.410 | 0.391 | | | | | | | | |
| BR | 0.743 | 0.693 | 0.509 | | | | | | | |
| BV | 0.559 | 0.643 | 0.285 | 0.636 | | | | | | |
| FA | 0.810 | 0.818 | 0.426 | 0.744 | 0.568 | | | | | |
| FI | 0.608 | 0.705 | 0.244 | 0.509 | 0.486 | 0.687 | | | | |
| PBC | 0.568 | 0.638 | 0.150 | 0.608 | 0.634 | 0.591 | 0.430 | | | |
| PEU | 0.548 | 0.612 | 0.221 | 0.694 | 0.675 | 0.585 | 0.446 | 0.788 | | |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| PU | 0.839 | 0.824 | 0.437 | 0.686 | 0.767 | 0.811 | 0.695 | 0.608 | 0.697 | |
| SUN | 0.523 | 0.614 | 0.409 | 0.651 | 0.483 | 0.613 | 0.388 | 0.678 | 0.720 | 0.646 |

**Cross-Loadings:** The cross loadings show how an indicator loads on the construct it underlies and on all other constructs in the study. As a threshold for discriminant validity to be established, an indicator should load considerably well and better on its own underlying construct than when it is loaded on any other construct in the study (Hair *et al.*, 2017). The results of this study indicate that all indicators loaded considerably well and better on their own underlying constructs than their loads on any other constructs in the study. This result is presented in Table 4.13.

**Table 4.13:** Cross loadings

| | BD | BI | BQ | BR | BV | FA | FI | PBC | PEU | PU | SUN |
|---|---|---|---|---|---|---|---|---|---|---|---|
| BD1 | 0.771 | 0.394 | 0.221 | 0.384 | 0.251 | 0.401 | 0.327 | 0.322 | 0.309 | 0.394 | 0.293 |
| BD2 | 0.677 | 0.403 | 0.229 | 0.332 | 0.246 | 0.428 | 0.373 | 0.212 | 0.188 | 0.439 | 0.214 |
| BD3 | 0.743 | 0.418 | 0.249 | 0.406 | 0.331 | 0.359 | 0.303 | 0.383 | 0.301 | 0.476 | 0.304 |
| BD4 | 0.722 | 0.446 | 0.183 | 0.443 | 0.365 | 0.548 | 0.385 | 0.400 | 0.366 | 0.502 | 0.270 |
| BI1 | 0.412 | 0.778 | 0.216 | 0.334 | 0.382 | 0.455 | 0.396 | 0.277 | 0.330 | 0.491 | 0.308 |
| BI2 | 0.427 | 0.721 | 0.179 | 0.411 | 0.366 | 0.488 | 0.433 | 0.424 | 0.357 | 0.449 | 0.388 |
| BI3 | 0.448 | 0.802 | 0.245 | 0.454 | 0.440 | 0.529 | 0.487 | 0.382 | 0.376 | 0.510 | 0.304 |
| BI4 | 0.511 | 0.845 | 0.297 | 0.493 | 0.392 | 0.557 | 0.525 | 0.514 | 0.419 | 0.574 | 0.448 |
| BQ1 | 0.087 | 0.187 | 0.559 | 0.114 | 0.143 | 0.084 | 0.106 | -0.058 | 0.009 | 0.216 | 0.075 |
| BQ2 | 0.229 | 0.273 | 0.823 | 0.331 | 0.180 | 0.283 | 0.171 | 0.024 | 0.090 | 0.255 | 0.257 |
| BQ3 | 0.263 | 0.253 | 0.795 | 0.357 | 0.152 | 0.297 | 0.148 | 0.076 | 0.211 | 0.234 | 0.275 |
| BQ5 | 0.308 | 0.197 | 0.820 | 0.323 | 0.162 | 0.309 | 0.163 | 0.158 | 0.171 | 0.279 | 0.282 |
| BR1 | 0.283 | 0.290 | 0.225 | 0.577 | 0.253 | 0.260 | 0.236 | 0.177 | 0.276 | 0.347 | 0.222 |
| BR2 | 0.397 | 0.287 | 0.257 | 0.579 | 0.297 | 0.344 | 0.236 | 0.240 | 0.336 | 0.310 | 0.267 |
| BR3 | 0.395 | 0.419 | 0.274 | 0.764 | 0.337 | 0.391 | 0.314 | 0.389 | 0.460 | 0.367 | 0.359 |
| BR4 | 0.341 | 0.437 | 0.274 | 0.757 | 0.358 | 0.505 | 0.321 | 0.341 | 0.267 | 0.373 | 0.375 |
| BR5 | 0.491 | 0.452 | 0.311 | 0.827 | 0.442 | 0.486 | 0.333 | 0.554 | 0.500 | 0.440 | 0.466 |
| BV3 | 0.261 | 0.289 | 0.144 | 0.282 | 0.763 | 0.258 | 0.243 | 0.314 | 0.309 | 0.430 | 0.183 |
| BV4 | 0.372 | 0.440 | 0.191 | 0.375 | 0.810 | 0.374 | 0.329 | 0.439 | 0.423 | 0.491 | 0.318 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| BV5 | 0.363 | 0.465 | 0.174 | 0.495 | 0.851 | 0.424 | 0.371 | 0.436 | 0.472 | 0.489 | 0.340 |
| FA1 | 0.495 | 0.392 | 0.192 | 0.364 | 0.187 | 0.646 | 0.389 | 0.177 | 0.149 | 0.358 | 0.130 |
| FA2 | 0.442 | 0.508 | 0.212 | 0.404 | 0.384 | 0.698 | 0.392 | 0.368 | 0.412 | 0.455 | 0.375 |
| FA3 | 0.342 | 0.391 | 0.280 | 0.427 | 0.330 | 0.705 | 0.353 | 0.318 | 0.284 | 0.447 | 0.300 |
| FA4 | 0.413 | 0.538 | 0.243 | 0.428 | 0.374 | 0.771 | 0.393 | 0.377 | 0.352 | 0.472 | 0.459 |
| FA5 | 0.504 | 0.505 | 0.263 | 0.446 | 0.315 | 0.801 | 0.515 | 0.412 | 0.410 | 0.541 | 0.390 |
| FI1 | 0.517 | 0.463 | 0.152 | 0.333 | 0.349 | 0.441 | 0.819 | 0.308 | 0.266 | 0.453 | 0.252 |
| FI2 | 0.296 | 0.453 | 0.127 | 0.295 | 0.296 | 0.444 | 0.775 | 0.236 | 0.264 | 0.419 | 0.185 |
| FI3 | 0.359 | 0.513 | 0.179 | 0.327 | 0.312 | 0.447 | 0.832 | 0.280 | 0.337 | 0.456 | 0.292 |
| FI4 | 0.377 | 0.506 | 0.165 | 0.357 | 0.396 | 0.511 | 0.837 | 0.308 | 0.304 | 0.480 | 0.303 |
| FI5 | 0.374 | 0.433 | 0.165 | 0.339 | 0.236 | 0.433 | 0.762 | 0.297 | 0.245 | 0.477 | 0.204 |
| PBC2 | 0.133 | 0.225 | -0.010 | 0.145 | 0.249 | 0.232 | 0.174 | 0.539 | 0.180 | 0.226 | 0.307 |
| PBC3 | 0.413 | 0.414 | 0.028 | 0.420 | 0.464 | 0.402 | 0.295 | 0.852 | 0.508 | 0.419 | 0.400 |
| PBC4 | 0.470 | 0.484 | 0.111 | 0.473 | 0.489 | 0.404 | 0.337 | 0.857 | 0.617 | 0.457 | 0.424 |
| PBC5 | 0.189 | 0.307 | 0.039 | 0.308 | 0.168 | 0.288 | 0.194 | 0.626 | 0.398 | 0.240 | 0.295 |
| PEU2 | 0.188 | 0.275 | 0.056 | 0.268 | 0.352 | 0.167 | 0.186 | 0.386 | 0.719 | 0.308 | 0.310 |
| PEU3 | 0.364 | 0.440 | 0.138 | 0.530 | 0.470 | 0.385 | 0.281 | 0.630 | 0.836 | 0.422 | 0.488 |
| PEU4 | 0.350 | 0.359 | 0.197 | 0.391 | 0.329 | 0.420 | 0.300 | 0.449 | 0.759 | 0.452 | 0.406 |
| PEU5 | 0.247 | 0.278 | 0.063 | 0.292 | 0.303 | 0.332 | 0.258 | 0.333 | 0.599 | 0.353 | 0.299 |
| PU1 | 0.551 | 0.512 | 0.282 | 0.416 | 0.505 | 0.487 | 0.428 | 0.317 | 0.369 | 0.777 | 0.347 |
| PU2 | 0.347 | 0.445 | 0.284 | 0.305 | 0.344 | 0.408 | 0.366 | 0.204 | 0.236 | 0.627 | 0.330 |
| PU3 | 0.451 | 0.489 | 0.223 | 0.425 | 0.437 | 0.490 | 0.454 | 0.393 | 0.467 | 0.770 | 0.391 |
| PU4 | 0.456 | 0.451 | 0.230 | 0.404 | 0.421 | 0.468 | 0.433 | 0.456 | 0.494 | 0.757 | 0.373 |
| PU5 | 0.449 | 0.437 | 0.170 | 0.319 | 0.384 | 0.428 | 0.367 | 0.351 | 0.306 | 0.671 | 0.287 |
| SUN2 | 0.238 | 0.331 | 0.200 | 0.224 | 0.292 | 0.293 | 0.177 | 0.319 | 0.340 | 0.327 | 0.739 |
| SUN3 | 0.353 | 0.389 | 0.288 | 0.477 | 0.267 | 0.432 | 0.247 | 0.421 | 0.445 | 0.369 | 0.812 |
| SUN4 | 0.289 | 0.378 | 0.227 | 0.438 | 0.289 | 0.383 | 0.299 | 0.411 | 0.456 | 0.436 | 0.824 |

**The variance inflation factor (VIF) and common method bias (CMB):** The variance inflation factor (VIF) is a measure of the degree of multicollinearity among a group of explanatory variables in a multiple regression model. While the VIF may not affect the explanatory power of a model, it greatly affects the statistical significance of the explanatory variables. A large VIF value of greater than 5 is an indicator of multicollinearity among the explanatory variables and therefore a value less that 5 is recommended (Latif *et al*., 2020). For this study, results in Table 4.14 show that all the VIF values for the outer model were less than 5, an indication that there were no problems of multicollinearity among the explanatory variables in both models.

**Table 4.14:** Collinearity statistics (VIF) for the outer model

| Construct | VIF value |
|---|---|
| BD1 | 1.465 |
| BD2 | 1.19 |
| BD3 | 1.391 |
| BI1 | 1.663 |
| BI2 | 1.411 |
| BI3 | 1.694 |
| BI4 | 1.826 |
| BQ1 | 1.171 |
| BQ2 | 1.737 |
| BQ3 | 1.927 |
| BQ5 | 1.808 |
| BR2 | 1.162 |
| BR3 | 1.561 |
| BR4 | 1.503 |
| BR5 | 1.652 |
| BV3 | 1.445 |
| BV4 | 1.405 |
| BV5 | 1.599 |
| FA1 | 1.380 |
| FA2 | 1.428 |
| FA3 | 1.453 |
| FA4 | 1.609 |
| FA5 | 1.635 |
| FI1 | 2.009 |

| | |
|---|---|
| FI2 | 1.764 |
| FI3 | 2.187 |
| FI4 | 2.206 |
| FI5 | 1.617 |
| PBC2 | 1.296 |
| PBC3 | 1.956 |
| PBC4 | 1.712 |
| PBC5 | 1.180 |
| PEU2 | 1.448 |
| PEU3 | 1.618 |
| PEU4 | 1.396 |
| PEU5 | 1.180 |
| PU1 | 1.690 |
| PU2 | 1.405 |
| PU3 | 1.760 |
| PU4 | 1.622 |
| PU5 | 1.326 |
| SUN2 | 1.299 |
| SUN3 | 1.438 |
| SUN4 | 1.418 |

Common method bias (CMB) on the other hand refers to a situation that occurs when data are collected from the same respondent for both the explanatory and dependent variables in the same measurement context, utilizing the same item context and comparable item attributes. This method problem is common in behavioural studies as was the case of this study, and it can be detected by assessing the values of VIF of the inner model. If the VIF values obtained from a comprehensive collinearity test exceed 3.3, it suggests that the model may be affected by common method bias, or pathological collinearity (Kock, 2015). For this study, all the VIF values of the inner model were lower than 3.3 as shown in Table 4.15, implying that the model was free of common method bias problem.

**Table 4.15:** Collinearity Statistics (VIF) for the inner model

| Construct relationship | VIF value |
|---|---|
| BD -> PU | 1.809 |
| BQ -> PU | 1.216 |
| BR -> BI | 1.695 |
| BR -> PU | 1.942 |
| BV -> BI | 1.703 |
| BV -> PU | 1.445 |
| FA -> PU | 2.190 |
| FI -> PU | 1.581 |
| PBC -> PEU | 1.303 |
| PEU -> BI | 1.800 |
| PU -> BI | 1.885 |
| PU -> PEU | 1.303 |
| SUN -> BI | 1.578 |
| SUN -> PU | 1.446 |

### 4.2.3 Structural model results (hypotheses' testing)

The results of the structural model analysis, conducted using PLS-SEM, are presented in Fig. 4.2, including the evaluation of path coefficients and hypothesis testing to assess the relationships among constructs and their significance. Also, the overall predictive ability of the model is assessed. The hypotheses ranged from 1 to 14 and the results for the tested hypotheses are presented in Table 4.16.

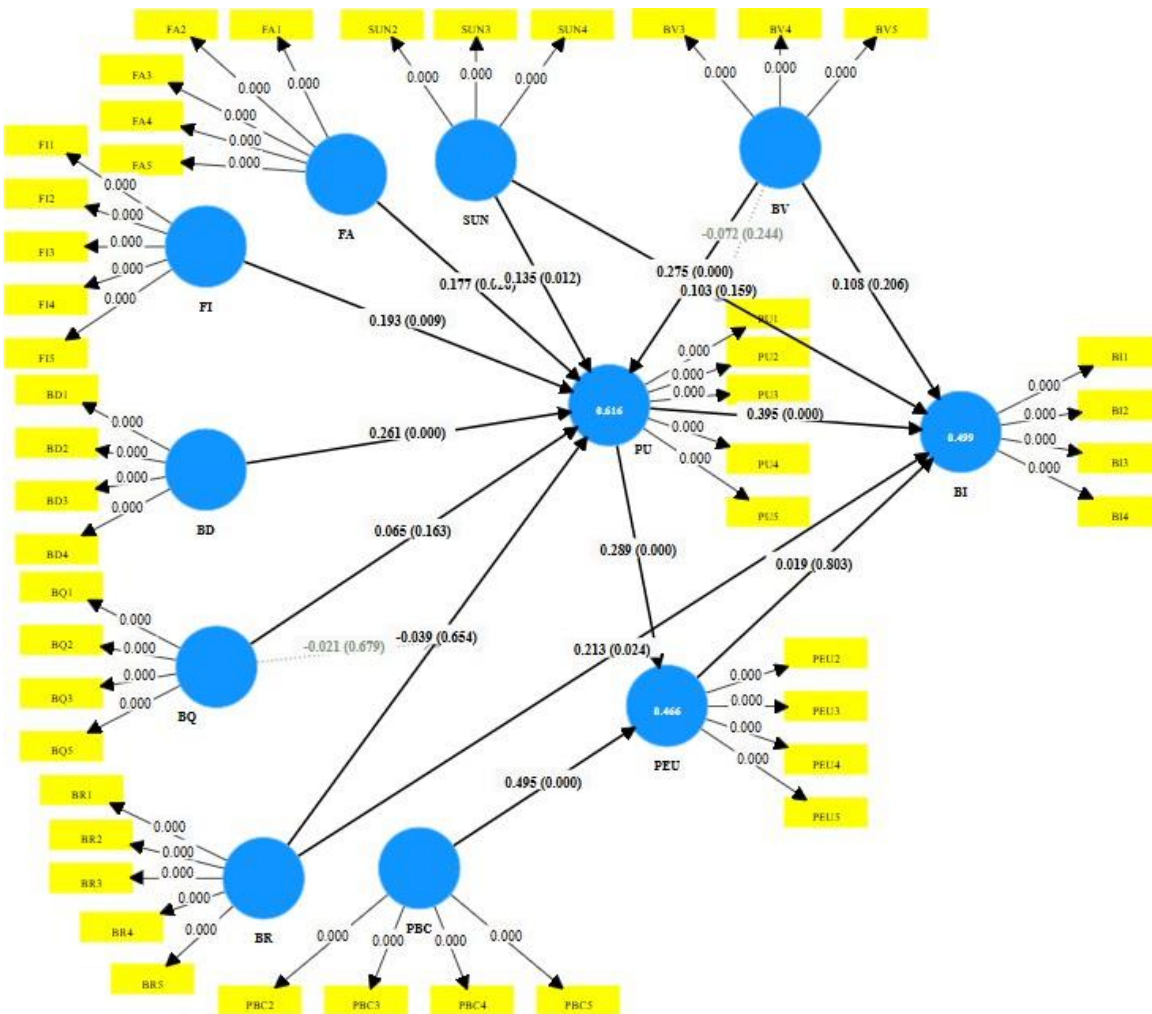


**Figure 4.2**: TAM2 structural model

**Direct and moderating effects of the independent variables on the dependent variables:** Overall, out of the 14 hypotheses that were tested in the multivariate regression analysis, 9 of them were supported while 5 of them were not supported. H1a evaluated whether subjective norm significantly and positively affected behavioural intention. The study results revealed that subjective norm had a positive but insignificant effect on behavioural intention (B=0.103, t=1.408, p=0.159), thus H1a was not supported. On the other hand, H1b evaluated whether subjective norm significantly and positively influenced perceived usefulness. Basing on the results, subjective norm had a positive and significant, at a 5% level, effect on perceived usefulness (B=0.135, t=2.520, p=0.012), hence H1b was supported. This implies that the effect of subjective norm on intention is indirect through perceived usefulness rather than direct. Since subjective norms is core construct in the Technology Acceptance Model, this result indicates that when individuals perceive that important others (e.g., peers, family, or social groups like farmer groups) believe they should use a technology, it enhances their perception of the technology's usefulness. This is consistent with previous research by Zhang *et al*. (2023a) that suggested subjective norms indirectly influence acceptance behaviour of pre-service teachers by altering perceptions of usefulness of artificial intelligence-enabled educational applications.

Additionally, H2 evaluated whether farmer attitude had a positive and significant effect on perceived usefulness of BCT, and from the results, this hypothesis was supported (B=0.177, t=2.231, p=0.026) at a 5% level of significance. This means that farmers had positive feelings about BCT which eventually enhanced their positive perception towards its usefulness in their barley value chain activities. This is likely because favourable attitude may have influenced the barley farmers to see the broader advantages of BCT such as transparency and efficiency. This in turn may have reduced their skeptism and made them more receptive to seeing the technology as useful. This finding aligns with a recent adoption study by Dong *et al*. (2022) where farmers' attitudes were found to positively influence perception towards usefulness of environmentally friendly agricultural technologies in China.

The effect of perceived farmer image on the perceived usefulness of BCT was evaluated in H3 to determine if it had a positive and significant impact. As a priori expected, perceived farmer image had a positive and significant effect on the perceived usefulness of BCT (B = 0.193, t = 2.610, p = 0.009) at the 1% level, supporting H3. This implies that farmers believed that using BCT enhances their social image and thus were more likely to perceive it as useful. As anticipated, this finding highlights how barley farmers' perceptions of their own social standing or reputation shaped their view of the benefits and practicality of accepting new technologies like blockchain. Similar to the findings of Mishra *et al*. (2024a), barley farmers who view themselves or are perceived by others as innovative and progressive are more likely to find new agricultural technologies useful. This is because such farmers believe that adopting new technologies will enhance their reputation or align with their self-image as forward-thinkers. They are therefore more likely to perceive these technologies as beneficial. These farmers associate technology use with improved farm productivity, social recognition, and economic gains, which further reinforces the perceived usefulness of the technology.

The evaluation in H4 examined whether blockchain technology result demonstrability had a positive and significant effect on perceived usefulness, and from the result it was shown that blockchain technology result demonstrability indeed had a positive and significant effect on perceived usefulness with (B=0.261, t=4.354, p=0.001). This result indicates that H4 was supported at 1% level of significance. Result demonstrability is the extent to which the results of using a technology are observable and communicable to others. This study's findings suggest that farmers found the results of using BCT tangible and easily communicable to others, making them perceive BCT to be useful. The visibility of the results could have been in form of improved efficiency, productivity, or cost savings in as afar as value chain operations are concerned. The current findings are consistent with studies on use of precision agriculture and e-Databases by faculty researchers where result demonstrability positively motivated perceived usefulness of the e-Databases (Izuagbe *et al.*, 2022).

The hypothesis in H5 evaluated whether barley output quality positively and significantly moderated the relationship between blockchain technology relevance (BR) and perceived usefulness (PU). However, the results indicated a negative and insignificant effect (B = -0.021, t = 0.414, p = 0.679). The results imply that variations in barley quality did not meaningfully influence how farmers perceived the usefulness of blockchain technology in the barley value chain. Alternatively, it may imply that farmers did not perceive a direct connection between improved barley quality and the relevance or benefits of blockchain technology. The results may be partly explained by the high-quality standards required by Company B, for barley crop output. Barley grain must meet various physiological and biochemical quality parameters, such as hectoliter weight, protein and carbohydrate content, specific moisture levels, grain uniformity, etcetera, before being accepted for malt production and brewing (Rani & Bhardwaj, 2021). However, not all of these quality parameters are directly influenced or achieved through blockchain technology use. Additionally, barley is highly sensitive to various postharvest handling processes, for which many farmers lack the necessary skills. As a result, lower-quality barley produced by farmers is often classified as grade two, fetching lower prices at Company B despite BCT's potential to enhance value chain performance. This finding contrasts with other TAM studies, such as those by Al-Gahtani (2016) and Venkatesh and Davis (2000), where output quality positively moderated the relationship between BCT relevance and perceived usefulness.

**Table 4.16:** Results of the hypotheses from the structural model

| Hypotheses | Path coefficients (B) | Standard deviation (SE) | T-statistics (t) | P values (p) |
|---|---|---|---|---|
| BD -> PU | 0.261 | 0.060 | 4.354 | 0.001 Supported |
| BR -> BI | 0.213 | 0.094 | 2.261 | 0.024 Supported |
| BR -> PU | -0.039 | 0.087 | 0.449 | 0.654 Not supported |
| BV -> PU | 0.275 | 0.062 | 4.434 | 0.001 Supported |
| FA -> PU | 0.177 | 0.079 | 2.231 | 0.026 Supported |
| FI -> PU | 0.193 | 0.074 | 2.610 | 0.009 Supported |
| PBC -> PEU | 0.495 | 0.063 | 7.845 | 0.001 Supported |
| PEU -> BI | 0.019 | 0.077 | 0.250 | 0.803 Not supported |
| PU -> BI | 0.395 | 0.100 | 3.959 | 0.001 Supported |
| PU -> PEU | 0.289 | 0.068 | 4.225 | 0.001 Supported |
| SUN -> BI | 0.103 | 0.073 | 1.408 | 0.159 Not supported |
| SUN -> PU | 0.135 | 0.054 | 2.520 | 0.012 Supported |
| BV x SUN -> BI | -0.072 | 0.062 | 1.164 | 0.244 Not supported |
| BQ x BR -> PU | -0.021 | 0.050 | 0.414 | 0.679 Not supported |

***Note:*** BD denotes result Demonstrability, PU denotes Perceived Usefulness, BR denotes BCT relevance to barley value chain, BI denotes Behavioural Intention, BV denotes Voluntariness in accepting BCT, FA denotes Farmer Attitude, and FI denotes Farmer Image, PBC denotes Perceived Behavioural Control, PEU denotes Perceived Ease of Use, SUN denotes subjective Norm, and BQ denotes Barley output Quality.

Equally, H6 evaluated whether blockchain technology relevance to the barley value chain (BR) had a positive and significant effect on perceived usefulness. However, the hypothesis was not supported (B = -0.039, t = 0.449, p = 0.654). The implication here is that farmers do not necessarily perceive blockchain technology as useful solely based on its relevance to crop value chains; other factors may also influence their perception. The possible explanations for this finding are as follows. First, since the technology relevance construct is a cognitive instrumental process, as conceptualized by Venkatesh and Davis (2000), rural barley farmers may have been unable to apply a mental representation to connect the goals of barley value chain to blockchain technology, in order to form a clear perception of its usefulness. Second, a lack of technical knowledge about how BCT works and how it could improve their operations in the initial stages of adoption may have further contributed to this result. Third, barley farmers might have associated blockchain technology with external control, monitoring, or additional compliance burdens imposed by Company B rather than viewing it as a tool that would directly benefit them. All these factors could weaken perceived usefulness of blockchain, even if it is considered relevant in the broader value chain. This study findings contradict previous research by Okcu *et al*. (2019) and Wu and Chen (2017), which found that technology-task relevance had a positive and significant influence on perceived usefulness. The possible reason for this contradiction could be attributed to differences in user-specific contexts between the present study and the aforementioned studies.

Nevertheless, in H7, blockchain technology relevance was found to have a positive and significant effect on farmers' behavioural intention (B=0.213, t=2.261, p=0.024), indicating that blockchain technology relevance had rather a direct effect on behavioural intention than indirectly through perceived usefulness. This finding implies that when farmers recognize the relevance of blockchain in crop value chains, they are more likely to express an intention to adopt or engage with it. The rationale behind this could be that blockchain was seen as highly relevant to barley farmers' operations, directly motivating their intentions to accept it, regardless of other factors like perceived usefulness. Further, the findings may reflect the early stages of blockchain adoption, where relevance is recognized but perceived usefulness has not yet fully materialized. As farmers gain experience and witness concrete benefits, their perception of usefulness may evolve, potentially strengthening adoption in the long run. These contrasting findings suggest a disconnect between farmers' recognition of blockchain's relevance and their early perception of its usefulness. While they acknowledge its role in the value chain, which encourages acceptance intentions, they may not yet see clear personal benefits. This highlights the need for contextual and tailored interventions, such as farmer education, demonstration projects, and incentives, to bridge the gap between relevance and perceived usefulness, ultimately fostering stronger adoption of blockchain technology in the barley value chain. While previous studies have examined the effect of technology relevance on perceived usefulness (Kemp *et al.,* 2019; Zarafshani *et al*., 2020), this study, to the researcher's knowledge, is the first to provide evidence of a direct relationship between technology relevance and behavioural intention.

Correspondingly, H8 evaluated whether perceived behavioural control (PBC) positively and significantly affected perceived ease of use (PEU) of blockchain technology. The study results supported this hypothesis at the 1% level of significance (B=0.495, t=7.845, p=0.001). The implication is that when farmers feel they have the necessary resources, knowledge, and ability to use blockchain technology, they are more likely to perceive it as easy to use. This is probably because barley farmers believed they could accept blockchain technology based on resources like possession of mobile phones, land, skills, and self-efficacy, which enhanced their perception of blockchain technology's ease of use. Additionally, the flexibility of blockchain technology to function on both sensory and keypad phones may have contributed to farmers perceiving it as easy to use. The result is consistent with the findings of Lopes *et al*. (2024), which noted that e-commerce shoppers who have control over the necessary resources are more likely to perceive AI enabled platforms as easy to use.

The hypothesis, H9, tested whether perceived usefulness of blockchain technology significantly affected perceived ease of use. Results showed a positive and significant effect (B = 0.289, t = 4.225, p = 0.001). This implies that when farmers recognize the benefits of blockchain technology, they are more likely to perceive it as easy to use. The plausible explanation for this is that barley farmers' positive perceptions of blockchain's usefulness in areas like transparency, efficiency, or market access, may have superseded their initial scepticism of its ease of use, motivating them to invest more effort and time into learning and using it, which in turn shaped their view of its ease of use. Instead of ease-of-use enhancing usefulness, as often suggested in technology adoption models (Davis, 1989; He *et al*., 2018), this finding indicates that usefulness itself may shape how easy farmers perceive the technology to be. This may also highlight that promoting the tangible benefits of BCT could indirectly improve its acceptance by making it seem more easier to use. Other studies have examined the role of perceived usefulness in shaping user attitudes, often finding a positive effect (Toraman, 2022). However, to the researcher' knowledge, this is the first study to explore its direct effect on perceived ease of use.

Further, H10 evaluated whether perceived usefulness had a positive and significant effect on behavioural intention to accept blockchain, and from the results, this hypothesis was supported at the 1% level of significance (B=0395, t=3.959, p=0.001). It is implied that when barley farmers perceive blockchain as beneficial and useful for improving productivity, and addressing value chain challenges, they were more likely to express a stronger intention to accept and use it. This could be because farmers may associate blockchain with tangible benefits such as better contract enforcement, reduced side-selling, and improved market access. If they perceive blockchain as a tool that fosters trust, reduces fraud, and enhances financial gains through transparency, their intention to adopt it is likely to increase. When technology directly addresses real challenges, farmers become more motivated to embrace it. Consistent with the hypothesis, this finding aligns with the TAM framework and previous research, where perceived usefulness has been found to positively influence technology acceptance intentions. For example, Victor *et al*. (2021) found that perceived usefulness significantly influenced Nigerian farmers' behavioural intentions to accept mobile applications. Similarly, Adnan *et al*. (2019) reported that perceived usefulness positively influenced Malaysian farmers' behavioural intentions to accept green fertilizer technology.

Regarding H11, it evaluated whether perceived ease of use had a positive and significant effect on behavioural intention to accept blockchain technology. The study's results unexpectedly revealed a positive but insignificant relationship with behaviour intention (B=0.019, t=0.250, p=0.803). This implies that in this smallholder farming context, how easy farmers perceive blockchain technology to be may not be a strong predictor of their intention to accept it. The conceivable account for this pattern is that, although perceived ease of use is a key construct in the TAM and TPB for positively and significantly predicting behaviour (Davis, 1989; Salloum *et al*., 2019), farmers may have prioritized the perceived usefulness of blockchain over its ease of use. Barley farmers might have been more concerned with how blockchain technology could directly benefit them, such as increasing productivity, eliminating exploitation by middlemen, or addressing input sourcing challenges, rather than how easy it is to use. Another possible explanation could be that Company B's blockchain tailored training and support systems, including on-farm visits and regular group training sessions, may have alleviated barley farmers' concerns about the technology's ease of use. As a result, ease of use became less critical in influencing acceptance intention compared to factors like perceived usefulness and relevance. This study's findings align with Al-Adwan *et al*. (2023), who reported that perceived ease of use did not significantly affect students' intentions to use metaverse-based learning platforms in Jordan

Voluntariness to accept blockchain was explored in H12 to evaluate whether it had a positive significant effect on perceived usefulness, and basing on the analysis results, H12 was supported (B=0.275, t=4.433, p=0.001) at the 1% level of significance. The implication here is that when farmers feel they are adopting a technology by choice rather than obligation, they are more likely to perceive it as useful. This study hypothesized a direct effect of voluntariness on perceived usefulness on the grounds that when individuals accept a technology voluntarily, they are intrinsically motivated to explore and utilize its capabilities. This idea is well supported in the literature on self-determination theory and intrinsic motivation in human behaviour (Deci & Ryan, 1985; Ryan & Deci, 2000; Deci & Ryan, 2013). This intrinsic motivation can lead to a more favourable perception of the technology's usefulness. In this context, farmers likely viewed their decision to accept blockchain technology as voluntary, free from external pressures, which encouraged them to explore blockchain benefits in barley value chain operations, thereby enhancing their perception of its usefulness. While previous studies have primarily examined the direct effect of voluntariness on behavioural intention, often finding significant positive relationships (Bervell & Arkorful, 2020*;* Park *et al.,* 2022), or its role as a moderator, as discussed in H13, this study provides novel insights into the relationship between voluntary technology acceptance and perceived usefulness among small-scale farmers, who are key stakeholders in agricultural value chains**.**

H13 evaluated whether voluntariness positively moderates the relationship between subjective norm and behavioural intention to accept blockchain. However, this hypothesis was not supported (B = -0.072, t = 1.164, p = 0.244). This implies that farmers' decision to accept blockchain was not significantly influenced by social pressures (subjective norms), regardless of whether the acceptance was voluntary or not. In other words, even if influential figures (such as, peers, extension officers, or company B staffs) encouraged blockchain technology adoption, voluntariness did not strengthen or weaken the effect of this social influence on farmers' behavioural intentions. It is possible that barley farmers' acceptance decisions might have been more driven by personal and economic considerations (like, perceived benefits, trust, or financial benefits), rather than social expectations or normative pressures. The voluntary nature of adoption may have led farmers to rely more on individual assessments or intrinsic motivation rather than conforming to social influence. These finding contrasts that of Venkatesh and Davis (2000), who found that voluntariness moderates the influence of subjective norms on behavioural intention. The reason for this contrast could be that unlike workplace environments, where employees may feel obligated to conform to social norms (as seen in Venkatesh & Davis, 2000), smallholder farmers may operate independently and base decisions on tangible benefits rather than peer pressure.

### 4.2.4 Model's explanatory power, predictive relevance, and out -of sample validation assessment results

The $R^2$ value indicates the variance in the dependent variable as explained by independent variables, and it shows the model's explanatory power or in-sample predictive power of the model. From this study's results in Table 4.17, the structural model as a whole explained 49.9% (R2=0.499) of the variance in barley farmers' behavioural intentions to accept blockchain technology. The explained variance for perceived usefulness of blockchain technology to the farmers was 61.6% (R2=0.616) while that of Perceived ease of use was 46.6% (R=0.466). This study being exploratory and social science based, all the $R^2$ values were deemed acceptable according to Hair *et al*. (2017), and Sarstedt *et al*. (2014) since they were above 10%. Correspondingly, $Q^2$ which measures the predictive relevance of the model was assessed and the revealed that all the values were greater than a threshold of zero (Hair *et al*., 2022) indicating that all the dependent variables in the model contributed to achieving the overall model's predictive relevance.

**Table 4.17:** Model's explanatory power ($R^2$), predictive relevance ($Q^2$), and out-of-sample validation ($Q^2$ predict)

| Dependent variables | $R^2$ values | $Q^2$ values | $Q^2$ predict values |
|---|---|---|---|
| BI | 0.499 | 0.470 | 0.451 |
| PEU | 0.466 | 0.427 | 0.428 |
| PU | 0.615 | 0.564 | 0.570 |

The $F^2$ value on the other hand is another measure of a model's explanatory power. $F^2$ indicates the change in the $R^2$ value of the dependent variables as a result of removal of one independent variables from the model, thus it indicates the effect size of each independent variable on the dependent variable. The $F^2$ presented in Table 4.18 reveal that only BR had a small effect size on PU ($F^2$=0.001) while the rest of the independent variables had medium to large effect size on PU. Whereas PBC had the largest effect size ($F^2$=0.352) on PEU, PEU had a small effect (0.015) on BI. Generally, considering Hair *et al*. (2021), only 3 independent variables had a small effect size on the dependent variables and the rest has medium and large effect sizes on the dependent variables.

**Table 4.18**: Model's explanatory power ($F^2$)

| Effect of IV on DV | f-square value |
|---|---|
| BD -> PU | 0.096 |
| BR -> BI | 0.049 |
| BR -> PU | 0.001 |
| BV -> PU | 0.129 |
| FA -> PU | 0.036 |
| FI -> PU | 0.062 |
| PBC -> PEU | 0.352 |
| PEU -> BI | 0.002 |
| PU -> BI | 0.169 |
| PU -> PEU | 0.120 |
| SUN -> BI | 0.015 |
| SUN -> PU | 0.033 |

Note: IV denotes independent variable, DV denotes Dependent variable

The model was also assessed for out of sample predictive power using the PLS predict approach in Smart PLS-SEM to ascertain the generalizability and practicability of the findings. Based on the results in Table 4.17, last column, the $Q^2$predict values for the dependent variables were all above the threshold of zero. Similarly, as shown in Table 4.19, Column 2, the $Q^2$predict values for the independent variables also exceeded this threshold, indicating that the model's constructs have strong out-of-sample predictive power.

**Table 4.19:** Out-of-sample validation (PLS-SEM versus LM prediction errors)

| Indicator | $Q^2$predict | PLS-SEM_RMSE | PLS-SEM_MAE | LM_RMSE | L _MAE |
|---|---|---|---|---|---|
| BI1 | 0.194 | 0.423 | 0.253 | 0.484 | 0.307 |
| BI2 | 0.270 | 0.431 | **0.339** | 0.460 | 0.330 |
| BI3 | 0.292 | 0.396 | 0.277 | 0.433 | 0.303 |
| BI4 | 0.351 | 0.381 | 0.267 | 0.404 | 0.285 |
| PEU2 | 0.136 | 0.431 | 0.326 | 0.467 | 0.341 |

| | | | | | |
|---|---|---|---|---|---|
| PEU3 | 0.407 | **0.797** | **0.611** | 0.780 | 0.567 |
| PEU4 | 0.222 | 0.424 | 0.261 | 0.477 | 0.289 |
| PEU5 | 0.128 | 0.408 | 0.297 | 0.465 | 0.330 |
| PU1 | 0.384 | 0.442 | 0.294 | 0.512 | 0.339 |
| PU2 | 0.218 | 0.516 | 0.395 | 0.544 | 0.408 |
| PU3 | 0.331 | 0.439 | 0.284 | 0.465 | 0.313 |
| PU4 | 0.310 | 0.463 | 0.287 | 0.524 | 0.351 |
| PU5 | 0.246 | 0.460 | 0.288 | 0.516 | 0.343 |

*Note:* The black bold values are for indicators that had higher PLS-SEM prediction errors than the LM prediction errors.

Further, the prediction errors in the PLS-SEM model, specifically the root mean squared error (PLS-SEM_RMSE) and mean absolute error (PLS-SEM_MAE) of the dependent variables' indicators, were compared against the benchmark values from a naïve linear model (LM), denoted as LM_RMSE and LM_MAE, respectively. As shown in Table 4.19, all but one PLS-SEM_RMSE value were lower than the corresponding LM_RMSE values, while all except two PLS-SEM_MAE values were lower than their respective LM_MAE values. According to Shmueli *et al*. (2019), this indicates that the model demonstrated medium to high predictive power. To address the two indicators with lower predictive power (PEU3 and BI2), the researchers examined potential data issues such as distribution anomalies, outliers, and indicator loadings. However, attempts to improve their predictive power through outlier treatment as recommended by Mooi *et al*. (2018) compromised the overall quality of the measurement model. Given that both indicators exhibited strong loadings on their respective constructs and retained medium predictive power, they were ultimately retained in the model.

### 4.2.5: Social norm analysis results with Smart PLS_SEM

Social norm analysis was carried out with an aim of exploring further the underlying drivers of barley farmers' behaviours regarding the intention to accept and use BCT. The analysis was estimated using PLS-SEM and the measurement model is presented in Figure 4.3.

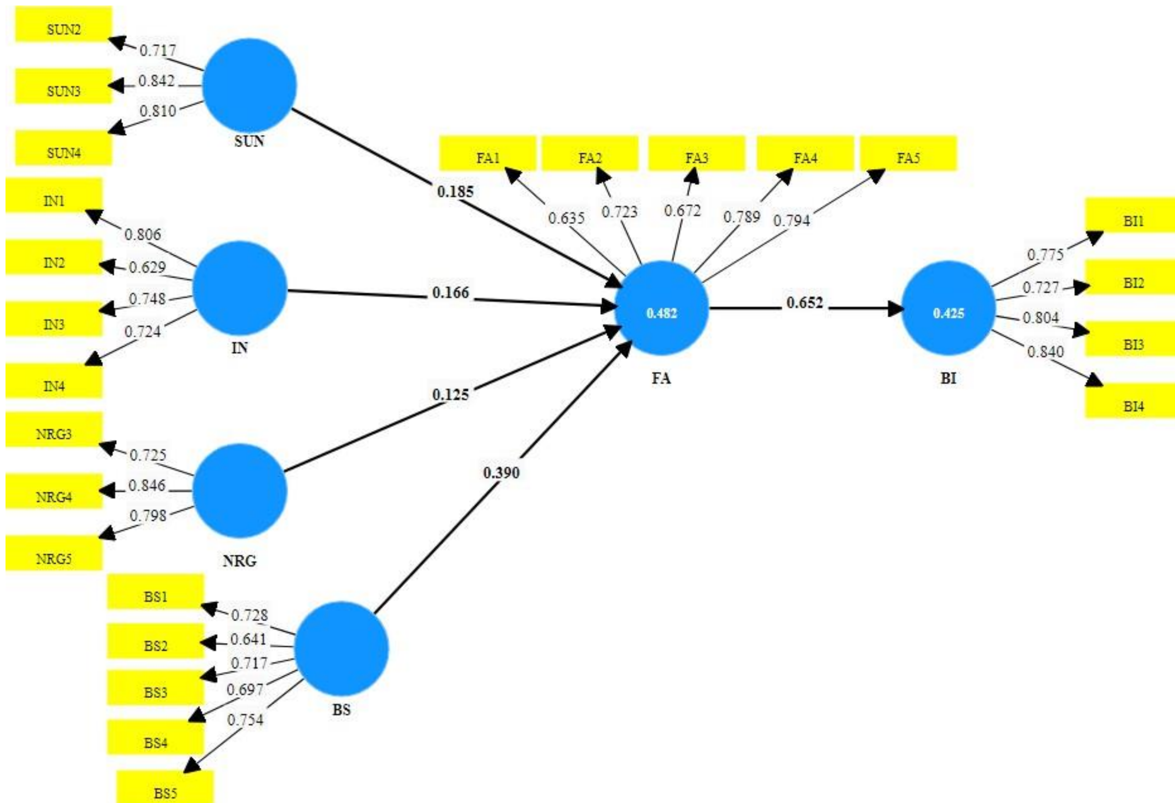


**Figure 4.3:** Measurement model of social norm analysis

**Model fit analysis:** The Standardized Root Mean Square Residual (SRMR), a key measure of model residuals, evaluates the average difference between observed and predicted correlations. Values ≤0.08 are generally recommended for a good fit (Hair *et al*., 2021; Henseler *et al*., 2016). In this model results, the SRMR values of 0.053 for the saturated model and 0.064 for the estimated model (Table 20) fall within the acceptable range, indicating a well-fitting model.

**Table 4.20:** Social norm analysis model fit analysis

| Model fit assessment criteria | Saturated model | Estimated model |
|---|---|---|
| SRMR | 0.076 | 0.079 |
| d_ULS | 1.739 | 2.350 |
| d_G | 0.517 | 0.555 |

| | | |
|---|---|---|
| Chi-square | 728.531 | 762.926 |
| NFI | 0.688 | 0.673 |

***Note:*** SRMR denotes Standardized Root Mean Square Residual; d_ULS denotes Squared Euclidean Distance; d_G= Geodesic Distance (both d_ULS and d_G are measures of exact fit), and NFI=Normed Fit Index.

**Social norm analysis measurement model assessment:** In order to report the quality of the reflective measurement model, some measures such as the outer loadings, reliability and validity, and Variance inflation factor (VIF) were assessed.

**Outer loadings:** The correlation matrix's outer loadings quantify how strongly each indicator is correlated with a given major construct. The outer loadings have values between -1.0 and 1.0; greater absolute values suggest a stronger association between the indicator and the underlying construct. Most research advises using indicator loading values greater than 0.70 (Pereira *et al*., 2024), while Hair *et al*. (2017) recommends loadings above 0.50 for social science based and exploratory research. This model being reflective, the indicators appeared in absolute terms with the constructs and therefore the indicators that were found to have lower loadings than 0.70 were eliminated. However, not all of them were eliminated as care was taken not to remove the indicators that would ultimately affect the reliability and validity of the model. As shown in Table 4.21 results, indicators SUN1, SUN 5, IN5, NRG1, and NRG2 were eliminated from the model while the rest of the indicator loadings were well above the 0.50 threshold.

**Table 4.21:** Outer loadings

| | BI | BS | FA | IN | NRG | SUN |
|---|---|---|---|---|---|---|
| BI1 | 0.775 | | | | | |
| BI2 | 0.727 | | | | | |
| BI3 | 0.804 | | | | | |
| BI4 | 0.84 | | | | | |
| BS1 | | 0.728 | | | | |
| BS2 | | 0.641 | | | | |
| BS3 | | 0.717 | | | | |
| BS4 | | 0.697 | | | | |
| BS5 | | 0.754 | | | | |
| FA1 | | | 0.635 | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| FA2 | | | 0.723 | | | |
| FA3 | | | 0.672 | | | |
| FA4 | | | 0.789 | | | |
| FA5 | | | 0.794 | | | |
| IN1 | | | | 0.806 | | |
| IN2 | | | | 0.629 | | |
| IN3 | | | | 0.748 | | |
| IN4 | | | | 0.724 | | |
| NRG3 | | | | | 0.725 | |
| NRG4 | | | | | 0.846 | |
| NRG5 | | | | | 0.798 | |
| SUN2 | | | | | | 0.717 |
| SUN3 | | | | | | 0.842 |
| SUN4 | | | | | | 0.81 |

**Construct reliability:** Construct reliability is used to describe how stable and consistent a construct is based on its indicators. It evaluates how well the indicators, reflect the latent construct that they are meant to measure. This study employed the common measures of Cronbach's alpha, composite reliability (rho_a), and composite reliability (rho_c). The values of these measures should be equal or above 0.70 but below 0.95 for reliability to be achieved (Hair *et al*, 2021). From the results obtained in Table 4.22**,** all the values were within the recommended thresholds affirming that construct reliability was achieved.

**Table 4.22**: Construct reliability

| | CA | rho_a | rho_c | AVE |
|---|---|---|---|---|
| BI | 0.795 | 0.800 | 0.867 | 0.620 |
| BS | 0.752 | 0.760 | 0.834 | 0.502 |
| FA | 0.775 | 0.790 | 0.846 | 0.526 |
| IN | 0.705 | 0.714 | 0.819 | 0.532 |
| NRG | 0.703 | 0.720 | 0.833 | 0.626 |
| SUN | 0.704 | 0.726 | 0.834 | 0.627 |

Note: CA denotes Cronbach's alpha, rho_a and rho_c denotes Composite reliability, and AVE denotes average variance extracted

**Construct validity:** The degree to which a latent construct accurately represents the concept it is designed to measure is known as construct validity. It ensures that the indicators in the model are accurate representations of the underlying concept. Ensuring the correctness and applicability of the inferences made from the model depends on construct validity. Validity can be convergent or discriminant. Convergent validity assesses how much variance is extracted as the indicators come together (converge) to explain the underlying latent construct, and this is measured by the average variance extracted (AVE). The threshold value for AVE is >0.5 (Hair. *et al*., 2017), and from the results, the AVE values obtained in Table 4.22 above for all the indicators were well above 0.50 threshold, therefore convergent validity was achieved.

**Discriminant validity:** Discriminant validity on the other hand assesses the discreteness of each construct in comparison with all other constructs in the model. For PLS-SEM to properly estimate the model, the constructs must have their individual identity and represent a unique aspect of the data which in turn helps to avoid multicollinearity problems. Three measures were used to assess the validity of the social norm analysis model namely Fornell and Larcker criterion, Heterotrait monotrait ratio (HTMTR), and Cross loadings. Fornell and Larcker criterion assess the square root of the shared variance among the constructs, and validity is achieved if the square root of variance of one construct (diagonal value) is larger than those of its associated contracts (vertical values) (Fornell & Larcker, 1981). As shown in Table 4.23 results, all the diagonal values were larger than the vertical values, hence discriminant validity was achieved.

**Table 4.23:** Fornell and Larcker Criterion test results for the social norm analysis model

| | BI | BS | FA | IN | NRG | SUN |
|---|---|---|---|---|---|---|
| BI | **0.787** | | | | | |
| BS | 0.623 | **0.708** | | | | |
| FA | 0.652 | 0.641 | **0.725** | | | |
| IN | 0.490 | 0.508 | 0.478 | **0.730** | | |
| NRG | 0.477 | 0.656 | 0.516 | 0.349 | **0.791** | |
| SUN | 0.463 | 0.459 | 0.479 | 0.381 | 0.416 | **0.792** |

The heterotrait monotrait (HTMT) ratio test of validity on the other hand compares the average correlations between indicators within a single construct (monotrait correlations) to average correlations between indicators across distinct constructs (heterotrait correlations). Compared to more conventional techniques like the Fornell-Larcker criterion, which might not always discover issues with concept overlap, the HTMT ratio is intended to detect discriminant validity issues more effectively. Henseler *et al*. (2015) suggests a threshold value of between less or equal to 0.85 for more theoretically parallel constructs and less or equal to 0.90 for more theoretically discrete constructs. The results of this study presented in Table 4.24 indicated that all the values were below the threshold level of 0.90 implying that the constructs within the model were not conflated and that discriminant validity was achieved.

**Table 4.24:** HTMT ratio test results of the social norm analysis model

| | BI | BS | FA | IN | NRG | SUN |
|---|---|---|---|---|---|---|
| BI | | | | | | |
| BS | 0.797 | | | | | |
| FA | 0.818 | 0.814 | | | | |
| IN | 0.643 | 0.678 | 0.628 | | | |
| NRG | 0.632 | 0.888 | 0.672 | 0.491 | | |
| SUN | 0.614 | 0.613 | 0.613 | 0.524 | 0.597 | |

Lastly on validity, the cross loadings measure was also used to assess the model's discriminant validity. Cross loadings test assesses the association between the indicator and the construct by checking whether the indicator loads considerably highest on its associated (mother) construct (primary loading) than the way it loads on any other construct in the model (cross loadings). For discriminant validity to be achieved, the primary loadings should be higher than the cross loadings (Rönkkö & Cho, 2022). From the cross loadings test results presented in Table 4.25, this threshold was achieved, implying that no indicator was measuring multiple constructs simultaneously.

**Table 4.25:** Primary and cross loadings test results of the social norm analysis model

| Indicators | BI | BS | FA | IN | NRG | SUN |
|---|---|---|---|---|---|---|
| BI1 | 0.775 | 0.396 | 0.459 | 0.377 | 0.350 | 0.312 |
| BI2 | 0.727 | 0.509 | 0.494 | 0.333 | 0.338 | 0.382 |

| | | | | | | |
|---|---|---|---|---|---|---|
| BI3 | 0.804 | 0.445 | 0.531 | 0.389 | 0.374 | 0.308 |
| BI4 | 0.840 | 0.597 | 0.561 | 0.440 | 0.434 | 0.447 |
| BS1 | 0.497 | 0.728 | 0.439 | 0.441 | 0.521 | 0.286 |
| BS2 | 0.368 | 0.641 | 0.360 | 0.229 | 0.439 | 0.212 |
| BS3 | 0.473 | 0.717 | 0.434 | 0.330 | 0.461 | 0.320 |
| BS4 | 0.375 | 0.697 | 0.478 | 0.401 | 0.479 | 0.379 |
| BS5 | 0.485 | 0.754 | 0.533 | 0.377 | 0.436 | 0.397 |
| FA1 | 0.391 | 0.375 | 0.635 | 0.293 | 0.233 | 0.133 |
| FA2 | 0.508 | 0.524 | 0.723 | 0.388 | 0.435 | 0.376 |
| FA3 | 0.391 | 0.350 | 0.672 | 0.236 | 0.320 | 0.304 |
| FA4 | 0.540 | 0.508 | 0.789 | 0.342 | 0.426 | 0.460 |
| FA5 | 0.505 | 0.526 | 0.794 | 0.439 | 0.412 | 0.397 |
| IN1 | 0.413 | 0.379 | 0.388 | 0.806 | 0.251 | 0.358 |
| IN2 | 0.261 | 0.241 | 0.320 | 0.629 | 0.221 | 0.228 |
| IN3 | 0.428 | 0.500 | 0.379 | 0.748 | 0.317 | 0.253 |
| IN4 | 0.303 | 0.339 | 0.292 | 0.724 | 0.218 | 0.260 |
| NRG3 | 0.329 | 0.390 | 0.322 | 0.260 | 0.725 | 0.302 |
| NRG4 | 0.416 | 0.544 | 0.442 | 0.259 | 0.846 | 0.405 |
| NRG5 | 0.381 | 0.597 | 0.444 | 0.310 | 0.798 | 0.278 |
| SUN2 | 0.331 | 0.306 | 0.301 | 0.217 | 0.329 | 0.717 |
| SUN3 | 0.388 | 0.384 | 0.434 | 0.347 | 0.284 | 0.842 |
| SUN4 | 0.378 | 0.394 | 0.386 | 0.322 | 0.387 | 0.810 |

**Multicollinearity and common method bias problem tests:** The model was also tested for collinearity and all the values of indicators obtained (Table 4.26) were below the threshold value of 5 (Henseler *et al*., 2015), implying that there was no problem of multicollinearity among the variables. The model was also tested for common method bias problem by assessing the VIF values of the inner (path) mode.

**Table 4.26:** Collinearity test results of the outer model

| Indicators | VIF value |
|---|---|
| BI1 | 1.663 |
| BI2 | 1.411 |
| BI3 | 1.694 |
| BI4 | 1.826 |
| BS1 | 1.467 |
| BS2 | 1.345 |
| BS3 | 1.460 |
| BS4 | 1.345 |
| BS5 | 1.437 |
| FA1 | 1.380 |
| FA2 | 1.428 |
| FA3 | 1.453 |
| FA4 | 1.609 |
| FA5 | 1.635 |
| IN1 | 1.565 |
| IN2 | 1.222 |
| IN3 | 1.418 |
| IN4 | 1.420 |
| NRG3 | 1.358 |
| NRG4 | 1.540 |
| NRG5 | 1.322 |
| SUN2 | 1.299 |
| SUN3 | 1.438 |
| SUN4 | 1.418 |

The VIF values of the inner model should be less or equal to 3.3 (Kock, 2015). The results in Table 4.27 show that all the VIF values were well below the threshold, hence common method bias was not a problem.

**Table 4.27:** Collinearity test results of the inner model

| Path relationships | VIF values |
|---|---|
| BS -> FA | 2.154 |
| FA -> BI | 1.000 |
| IN -> FA | 1.400 |
| NRG -> FA | 1.809 |
| SUN -> FA | 1.355 |

**Social norm analysis structural model analysis hypotheses' testing results:** The results of the hypotheses that were tested using partial least squares structural equation modelling are presented in Figure 4.4 and Table 4.28.

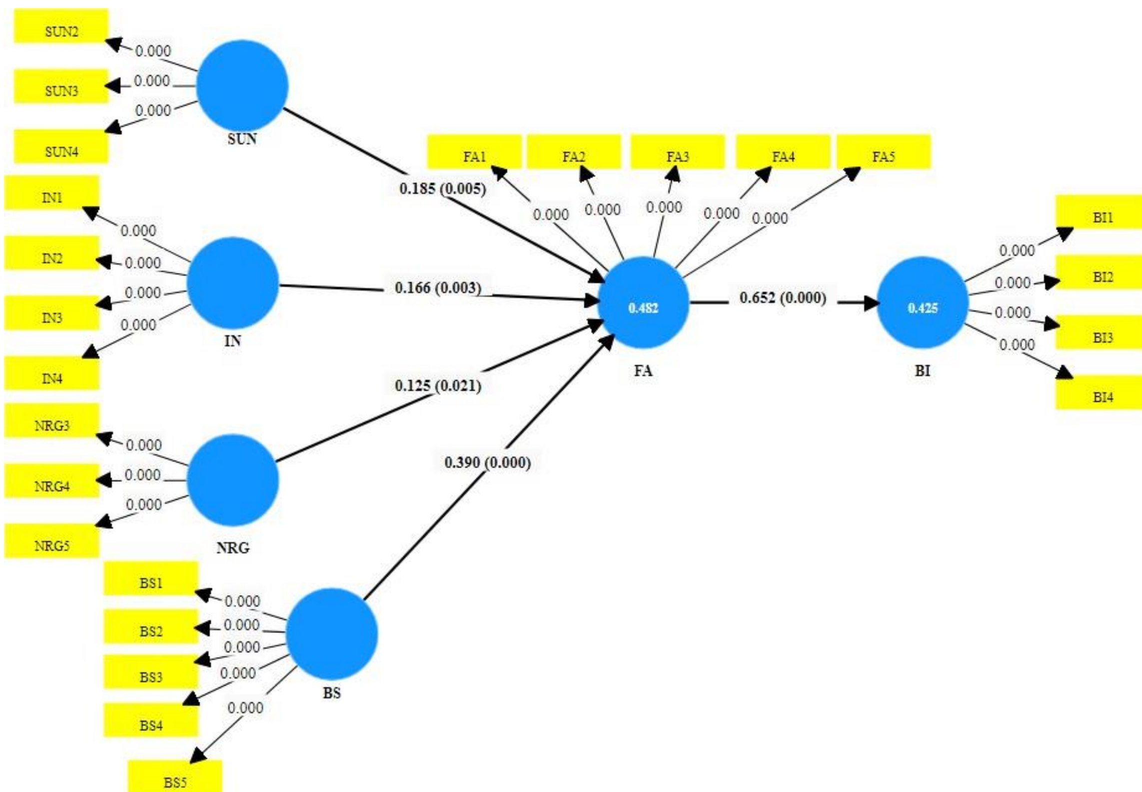


**Figure 4.4:** Structural model of social norm analysis

Based on the results, all the hypotheses as a priori expected were supported. S_H1 evaluated whether subjective norm had a positive and significant effect on farmers' attitudes. This hypothesis was supported at a 1% level of significance (B=0.185, t=2.832, p=0.005). The findings show that social influence from peers, family, and other farmers' groups has a beneficial effect on how each farmer perceives blockchain, which may then influence how they feel about the same. Farmers were encouraged to form positive attitudes regarding blockchain because they thought it was a wise choice since these social influencers supported it. This could have been possible because barley farmers live in Sebei farming community where the decisions of other community members matter, when it comes to new interventions like blockchain. This result agrees with Kelly and Palaniappan (2023), that social influence positively affects mobile money users' attitudes. While previous agricultural technology adoption research has focused on the direct effect of subjective norms on behavioural intention (Tama *et al*. 2021; Wang *et al*. 2019), and subjective norms on perceived usefulness (Ulhaq *et al*. 2022), this study provides fresh insights into the understanding of the direct influence of subjective norms on small holder farmers' attitudes towards technology acceptance.

**Table 4.28:** Path coefficients in the social analysis relationship with behavioural intention

| Hypotheses | Beta coefficient (B) | Standard deviation (SE) | T statistics (t) | P values (p) |
|---|---|---|---|---|
| BS -> FA | 0.390 | 0.074 | 5.265 | 0.001 Supported |
| FA -> BI | 0.652 | 0.055 | 11.857 | 0.001 Supported |
| IN -> FA | 0.166 | 0.056 | 2.979 | 0.003 Supported |
| NRG -> FA | 0.125 | 0.054 | 2.307 | 0.021 Supported |
| SUN -> FA | 0.185 | 0.065 | 2.832 | 0.005 Supported |

***Note:*** BS denotes Behavioural Sanctions, FA denotes Farmer Attitude, BI denotes Behavioural Intention, IN denotes Injunctive Norms, NRG denotes Normative reference Groups, while SUN denotes subjective Norm.

The Hypothesis S_H2 evaluated whether injunctive norm had a positive and significant influence on farmers' attitudes towards blockchain technology, and this was supported at a 1% level of significance (B=0.166, t=2.979, p=0.003). This suggests that social pressures, particularly those regarding what farmers perceive as socially approved or accepted behaviour, played a crucial role in shaping their willingness to accept blockchain technology. A possible explanation for this is that farmers perceived that blockchain technology, introduced by trusted long-term buyers like Company B, was likely to benefit the entire value chain. As a result, they viewed accepting it as socially acceptable and okay, even though they were unsure if it would positively impact their value chain operations. The perception that accepting blockchain was a socially expected and approved decision could have ignited positive feelings and beliefs among farmers toward blockchain. Mishra *et al*. (2024a) revealed similar results, indicating that companies that take the lead in integrating blockchain technology into supply chains influence other firms to view blockchain technology as beneficial and a valuable factor for successful supply chain management. Also, research by Nystrand and Olsen, (2020) found injunctive norms to positively influence the attitudes and intentions of Norwegian consumers to consume functional foods.

The S_H3 investigated whether normative reference groups had a positive significant effect on farmers' attitudes towards blockchain technology. The social norm analysis model results supported this hypothesis at a 5% level of significance (B=0.125, t=2.307, p=0.021). This implies that barley farmers' attitudes towards blockchain technology were positively motivated by the behaviours (acceptance) of reference groups notably progressive farmers, Company B mid-level managers and field staff, mainstream agricultural extension officers at sub-counties and parishes. This is because farmers often trust and look to these groups for guidance on what technologies to accept, especially when faced with uncertainties or complexities in use of technologies like blockchain. Barley farmers were comparing their beliefs and intentions about blockchain technology with those of referents, and this social pressure to align with others subsequently led to more favourable attitudes toward accepting blockchain technology. The current findings are consistent with those of Pfeiffer *et al*. (2021) who reported that social trust in farmers and other respected community members positively influenced the attitudes of the general public of Germany to accept digital farming technologies. Relatedly, Zeweld *et al*. (2019) revealed that relational capital akin to reference groups positively influenced the attitudes of Ethiopian smallholder farmers toward farming risks.

Behavioural sanctions were hypothesised in S_H4 to have a positive and significant effect on farmer attitudes towards blockchain technology. The analysis results supported this hypothesis at a 1% level of significance (B=0.390, t=5.265, p=0.001). This suggests that informal consequences for non-acceptance played a crucial role in shaping farmers' perceptions of the technology. It implies that when farmers perceive the acceptance of blockchain technology as being encouraged through community norms, they may develop a more favourable attitude toward its acceptance. One possible explanation is that barley farmers, being part of a farming community where some had already adopted blockchain technology, may have felt socially obligated to do the same. Those who had not yet adopted the technology might have feared disapproval or social exclusion from their peers. This social obligation likely motivated them to shift their attitudes and become more favourable towards accepting the technology. The existence of social sanctions in the study area increased the likelihood that farmers viewed accepting blockchain technology as socially desirable. This positive association emerged because failing to accept the technology could have had consequences like being left behind or losing respect within their community. The findings are in line with Liu *et al*. (2018) results where social sanctions positively influenced sheep farmers' attitudes towards farm inspections in England. In contrast to our findings, Zinngrebe *et al*. (2017) discovered that the fear of sanctions had a negative effect on German farmers' attitudes and choices regarding green ecological conservation practices. Instead of encouraging compliance, these sanctions fostered resistance and reluctance among farmers to adopt such practices.

Social norms' collective positive impact on barley farmers' attitudes led to attitudes eventually having a statistically positive and significant influence on farmers' intentions to adopt blockchain technology. This was investigated in S_H5, where it was predicted that attitudes would significantly and favourably influence behavioural intention. At the 1% level of significance, this hypothesis was supported (B=0.652, t=11.857, p=0.002). This suggests that the more favourable a farmer's perception of blockchain technology, the higher their likelihood of intending to use it in their barley value chain activities. The magnitude and significance of the relationship underscore the importance of shaping positive attitudes to drive acceptance. A possible explanation for this result is that farmers who perceive blockchain technology as beneficial, efficient, and reliable are more motivated to integrate it into their practices. This finding fits with the theory of planned behaviour which posits that attitudes positively motivate behavioural intentions (Ajzen, 1996). The findings further align with most technology adoption studies in various domains including agrifood sector (Alavion *et al*., 2017; Castiblanco Jimenez *et al*., 2021), business and marketing (Sciarelli *et al*., 2022), and consumer behaviour studies (Pérez-Sánchez *et al*., 2021) where attitudes have been found to positively influence participants' behavioural intentions.

Social norm analysis model's explanatory power, predictive relevance and out of sample validation assessments: The model's explanatory power was assessed by two measures namely the $R^2$ values and the $F^2$ values. The former measures the variance in the dependent variable explained by the independent variables in the model. The results presented in Table 4.29 indicate that the whole model explained 42.5% of the farmer's behavioural intentions (R2=0.424) to accept BCT, while farmers' attitude was explained at 48.2% ($R^2$=0.482). These levels are all acceptable in social science and exploratory research since they are well above 10% (Hair *et al*., 2017; Sarstedt *et* *al*.,2014). Similarly, predictive relevance of the was established from the results since all the $Q^2$ values were greater than the threshold of 0 (Hair & Alamer, 2022).

**Table 4.29:** Explanatory power, Predictive relevance, and out of sample validation

| Dependent variables | $R^2$ values | $Q^2$ values | $Q^2$ predict for the dependent variables | $Q^2$ predict for the dependent variable items |
|---|---|---|---|---|
| BI | 0.425 | 0.391 | 0.391 | 0.186-0.330 (B1-B4) |
| FA | 0.482 | 0.444 | 0.444 | 0.104-0.318 (F1-F4) |

The model's out-of-sample predictive power was evaluated using the PLS-Predict approach in Smart PLS-SEM to determine the generalizability and practical applicability of the findings. As shown in Table 4.29 (third and last columns), the $Q^2$predict values for both the dependent variables and their individual items exceeded the zero threshold, confirming that the model's constructs possessed strong out-of-sample predictive power.

Effect size ($F^2$) assessment results of SNA model: $F^2$ value measures the effect size or the change in $R^2$ value of a dependent variable as a result of removal of one independent variable from the model. Farmer attitude being the sole independent variable for Behavioural intention, its effect size was considerably larger ($F^2$=0.740), behavioural sanctions ($F^2$ =0.136) and normative reference groups ($F^2$ =0.017) had a small effect size while injunctive norm ($F^2$ =0.038) and subjective norm ($F^2$ =0.049) had a medium effect size (Hair *et al*., 2021; Rigdon *et al*., 2017). The results are presented in Table 4.30.

**Table 4.30:** Effect size test results of the social norm analysis model

| Relationships | $F^2$ value |
|---|---|
| BS -> FA | 0.136 |
| FA -> BI | 0.740 |
| IN -> FA | 0.038 |
| NRG -> FA | 0.017 |
| SUN -> FA | 0.049 |

## 4.3 Factors affecting adoption and usage extent of blockchain technology

The aim of objective two was to determine the factors affecting the decision to adopt blockchain and the usage extent. It was analysed in two separate stages (hurdles) using the Cragg's double hurdle model. The outcome variable in the first hurdle, the decision stage of whether to adopt blockchain or not, was binary; *BCTadopt* (whether a farmer was a blockchain adopter BCTadopt=1, or otherwise BCTadopt=0), and was modelled using probit. The second hurdle estimated the extent of use of blockchain technology and was modelled by censored Tobit model using a continuous variable which was the number of seasons an adopting farmer produced and supplied through blockchain since its introduction in 2019.

### 4.3.1 Diagnostic tests on variables used in Double hurdle model

In order to get unbiased model estimates, diagnostic tests such as multicollinearity and heteroskedasticity were done on variables that were selected to be used in the double hurdle model. The variance inflation factor (VIF) test for multicollinearity was conducted on the continuous variables while pairwise correlation test was conducted on the categorical variables. Multicollinearity is a statistical problem that arises when a model's explanatory variables are highly linearly intercorrelated which may lead to biased overall model estimates (Bayman & Dexter, 2021). The results of multicollinearity test for this study as presented in Table 4.31 revealed that all the explanatory variables had VIF values between 1.022 and 1.729 which are below the 5 to 10 threshold value (Kim, 2019). The overall mean VIF value was 1.239.

**Table 4. 31:** Variance inflation factor

| | VIF | 1/VIF |
|---|---|---|
| Production costs (USD) | 1.729 | 0.578 |
| Marketing costs (USD) | 1.588 | 0.63 |
| Land size owned by a farmer (acres) | 1.382 | 0.724 |
| BCT related training costs (USD) | 1.276 | 0.784 |
| Age (years) | 1.263 | 0.792 |
| BCT initial cost (USD) | 1.154 | 0.866 |
| Years of Schooling | 1.136 | 0.88 |
| freq BCTtraining | 1.112 | 0.899 |
| Distance to Company B buying centre (KM) | 1.093 | 0.915 |

| | | |
|---|---|---|
| Distance to trading centre Mins | 1.069 | 0.935 |
| Extension services frequency | 1.05 | 0.953 |
| Extension services costs | 1.022 | 0.978 |
| Mean VIF | **1.239** | . |

The results of the pairwise correlations in Table 4.32 further revealed no correlations among the explanatory categorical variables as all the pairwise correlation values were less than the threshold of 0.8 (Shrestha, 2020)

**Table 4. 32:** Pairwise correlations for categorical variables used in the model

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| (1) | 1.000 | | | | | | | |
| (2) | 0.271 | 1.000 | | | | | | |
| (3) | 0.181 | 0.061 | 1.000 | | | | | |
| (4) | 0.031 | 0.008 | 0.066 | 1.000 | | | | |
| (5) | 0.052 | -0.004 | 0.011 | -0.012 | 1.000 | | | |
| (6) | -0.047 | 0.019 | 0.078 | 0.122 | 0.141 | 1.000 | | |
| (7) | 0.064 | 0.048 | 0.020 | 0.160 | -0.001 | 0.001 | 1.000 | |
| (8) | -0.072 | -0.012 | -0.051 | 0.488 | -0.253 | -0.059 | 0.047 | 1.000 |

Note: 1=Sex, 2=Marital status, 3=Group membership (yes/No), 4=Network stability (Yes/No), 5=Power connection (Yes/No), 6=Land tenure, 7=BCT compatibility, 8=Phone ownership

Additionally, a heteroscedasticity test was performed. In regression models, heteroskedasticity occurs when the variance of the residuals, or errors, varies at different levels of the explanatory variables, violating one of the main assumptions of linear regression that the variance of the error terms is constant (Schmidt & Finan, 2018). Estimates derived from OLS (Ordinary Least Squares) are less reliable and efficient when heteroskedasticity is present as it causes skewed standard error estimates and compromises the validity of hypothesis testing. Although the coefficients themselves are still objective, inferences drawn from them are no longer accurate (Das, 2019) .

Both the White test and the Breusch-Pagan tests, which are the most popular tests for heteroscedasticity, were applied in this study, and the results are presented in Table 4.33**.** Based on the null hypothesis that the residuals are homoscedastic, the Breusch-Pagan Test determines if the squared residuals from a regression model are associated with the independent variables; a significant p-value indicates heteroskedasticity. In contrast to the Breusch-Pagan test, the White test is a more universal test. Instead of assuming a particular heteroskedasticity form, it examines whether the squared residuals are connected to the squares or interactions of the explanatory variables. Based on the findings, the χ2 value was significant (p=0.001, leading us to reject the null hypothesis of homoskedasticity. Heteroskedasticity-robust standard errors were utilized to address the heteroscedasticity issue found without altering the model's specifications (Clar, 2023).

**Table 4.33:** Heteroskedasticity test results using the White test

| Source | chi2 | df | P |
|---|---|---|---|
| Heteroskedasticity | 486.160 | 185 | 0.001 |
| Skewness | 93.220 | 19 | 0.001 |
| Kurtosis | 6.860 | 1 | 0.009 |
| **Total** | **586.250** | **205** | **0.001** |

Note: chi2 = chi-square; df = degrees of freedom, and p value = level of significance

### 4.3.2 Double hurdle model estimate results

From the results presented in Table 4.34, combining the log-likelihood values determined in the first and second hurdles yielded the log-likelihood of the Craggit. This log pseudolikelihood value was -202.65155 and was significant at 1% level, with a Wald $Chi^2$ value of 14928.24 (p=0.000). This high level of significance implies that the model's parameters effectively explain the outcomes, validating the inclusion of the selected variables. The strong Wald Chi-square statistic suggests that some explanatory variables meaningfully influence results in both hurdles, with a very low probability (less than 1%) that these findings are due to chance, offering robust support for the relationships tested in the model. Appendix B displays the maximum likelihood estimates obtained using the Craggit command.

### 4.3.3 Factors affecting the decision to adopt blockchain technology

The marginal effects estimates of the factors influencing a barley farmer's decision to adopt blockchain, which represents the first stage of the DHM, are presented in Table 4.34. Marginal effects estimates are preferred over the raw coefficients in the first hurdle because the latter are produced from a non-linear model (Probit). Thus, the raw coefficients indicate just the direction of effect of the explanatory variables on the outcome variable but not the magnitude of effect/probability change (Burke, 2009).

**Table 4.34:** Factors affecting decision to adopt blockchain technology

| Variable | Marginal effects(dy/dx) | Standard error | p-value (P>z) |
|---|---|---|---|
| Sex (1=Male, 0=Female) | 0.0854891 | 0.2599316 | 0.742 |
| Age of the respondent (years) | -0.0087242 | 0.0065093 | 0.180 |
| Education level (years in school) | 0.0173035 | 0.0173302 | 0.318 |
| Marital status (1=Married, 0=single/widowed) | -3.105226 | 0.6549261 | 0.000*** |
| Extension services (Frequency of visits) | -0.2107299 | 0.0539716 | 0.000*** |
| BCT training (number of times trained) | 5.931999 | 0.1034075 | 0.000*** |
| Group membership (1=Yes, 0=Otherwise) | -0.2090458 | 0.1745043 | 0.231 |
| BCT training cost (USD) | -0.0003772 | 0.0000278 | 0.000*** |
| Network stability (1=Stable, 0=Otherwise) | 3.314731 | 0.4945346 | 0.000*** |
| Production costs (USD) | 3.98e-07 | 1.88e-07 | 0.034** |
| Power connectivity | 0.0835549 | 0.178834 | 0.640 |
| Land tenure | -0.7729772 | 0.2987934 | 0.010** |
| Distance to Company B buying centre (KM) | -0.0451494 | 0.0220534 | 0.041** |
| Land size owned by a respondent (Acres) | 0.1120044 | 0.0469859 | 0.017** |
| Initial cost of BCT app (USD) | -0.0023812 | 0.0004699 | 0.000*** |
| BCT compatibility (1=Compatible,0=Otherwise) | 10.37776 | 0.3537005 | 0.000*** |
| Costs of extension (USD) | -1.77e-06 | 2.26e-06 | 0.434 |
| Marketing costs (USD) | -1.37e-06 | 6.21e-07 | 0.027** |
| Phone ownership (1=Yes, 0=Otherwise) | 1.422152 | 0.5280234 | 0.007** |
| Constant | -7.257821 | 0.6615716 | 0.000*** |
| Observations | 490 | | |
| Wald $Chi^2(19)$ | 14928.24 | | |
| Prob>$Chi^2$ | 0.0000 | | |
| Log pseudolikelihood | -202.65155 | | |

Note: ***, **, * denote significance level at 1%, 5%, and 10% levels respectively

1 USD = Ugx 3,682/= as of 2025

Marital status negatively and significantly influenced a barley farmer's decision to adopt blockchain technology at the 1% significance level. Being married reduced the probability of adopting blockchain technology by 3.1%, contrasting with previous findings (Gebre *et al.*, 2019; Atube *et al*. 2021), which often showed that married farmers were more likely to adopt agricultural technologies. The current findings present a new insight into the relationship between marital status and the adoption of agricultural technologies such as blockchain. The credible elucidation for this pattern may be the social vulnerability that single-headed households face and their absolute resolve to improve on their farming outcomes, prompting them to have a higher propensity to adopt blockchain to their comparable married-headed households. Conversely, married household heads may need to make joint decisions, potentially delaying technology adoption. The study findings align with those of Badstue *et al*. (2020) who found that Ethiopian single women farmers were more likely than married farmers to be creative and use new technologies.

Provision of agricultural extension services to smallholder farmers has been found to play a dynamic role in enhancing the adoption of agricultural technologies in several adoption research (Chelang'a *et al.*, 2023; Pan *et al.*, 2018; Tu *et al.*, 2018). However, this study found that the frequency of extension services, represented by the number of extension officer visits to the farm, had a significantly negative effect on blockchain technology adoption at the 1% significance level. A unit increase in the number of extension visits reduced the probability of adopting blockchain technology by 21%. Farmers reported that conventional extension officers delivered the same standard agronomy and post-harvest handling training, without introducing any new ideas or information specifically related to blockchain technology. This suggests that farmers may have experienced extension fatigue, as the visits offered limited information on blockchain adoption, making frequent visits less motivating for adoption. Wordofa *et al*. (2021) also observed that frequent extension visits din not improve adoption of agricultural technologies in Eastern Ethiopia. The current finding is further corroborated by Danso-Abbeam *et al*. (2018), who reported that the adoption of most farm technologies in Ghana was less successful when extension services were provided often but with an excessive emphasis on one aspect, such as market linkage, rather than balancing it with information on technology adoption.

Blockchain technology tailored training given before or after farmer enrolment on blockchain software app had a positive statistically significant effect on adoption of blockchain at a 1% level of significance. This suggests that an additional number on the blockchain tailored trainings received by the farmer, increased the probability of a farmer adopting blockchain by 5.9%. During the blockchain technology trainings, farmers were provided with knowledge on the benefits of incorporating blockchain in their value chain activities which would potentially encourage them to adopt. AlShamsi *et al*. (2022) highlight that one of the greatest barriers to adoption of blockchain technologies is a lack of user knowledge and experience which could be lessened through tailored training. Moreover, Silva *et al*. (2024) emphasized that tailored education and training could assist stakeholders and organizations in overcoming obstacles like technological complexity, which frequently prevents blockchain adoption.

While blockchain-specific training was essential for increasing adoption, the cost associated with it was not. The results of this study on blockchain training costs indicated a statistically significant but negative effect, at a 1% level of significance, on barley farmers' adoption of blockchain. It was observed that an extra USD spent on blockchain tailored training decreased the adoption by 0.03%. With the financial constraints that many smallholder agribusinesses face, it is likely that high BCT training costs could act as a significant barrier, as farmers often have limited disposable income and prioritize immediate needs, such as inputs, Labor, and household expenses, over investments in new technologies. This study's results are consistent with that of Chakraborty and Paul (2023) which found that organizations with tight budgets are less likely to adopt and implement blockchain technologies due to the high cost of blockchain-tailored training. This situation may be particularly dire for smallholder barley farmers in Uganda.

Regarding mobile network connectivity, a more stable mobile network had a positive and significant effect on BCT adoption at the 1% significance level, with each unit increase in network stability raising the likelihood of adoption among barley farmers by 3.3%. Blockchain software app was connected on the mobile phones of smallholder farmers, Company B field staff and middlemen, and its interface loaded on computer systems of Company B at buying centres. Thus, the stability of the network underscored its importance to the whole process of adoption since exchange of information among the barley value chain stakeholders could only be possible with stable network. Alammary *et al*. (2019) also noted that the smoother execution of blockchain enabled technologies, such as smart contracts, which are essential in financial and legal blockchain applications, is ensured by the stability of mobile phone network.

Production costs were observed to have a positive and significant effect on the decision to adopt blockchain technology at a 5% level of significance. An additional cost of production by 1 USD to the farmer increased the probability of adopting blockchain by 3.9%, keeping other factors constant. In this instance, it appears that farmers adopted blockchain due to the economic pressure of high production costs since it offered the benefit of early season access to production inputs, for which payment was contingent upon delivery of barley harvest to Company B buying centres. Farmers were therefore released from the requirement to pay for production inputs, which would have interfered with timely operations if farmers are financially limited. This result supports the findings of Chiaraluce *et al*. (2024), who found that blockchain lowers transaction and production costs of firms in developing economies.

For this study, land tenure was categorized as a dummy variable, with 1 representing customary tenure and 0 representing non-customary (commercial) tenure. According to the 1998 Land Act of Uganda, land tenure falls under four categories: Leasehold, Mailo, Freehold, and Customary. The first three are obtained on a commercial basis, while the fourth is purely customary. Land tenure had a significant influence on a farmer’s decision to adopt blockchain technology. Specifically, farmers with customary land tenure were 77.3% less likely to adopt blockchain compared to those with non-customary (commercial) land tenure. This negative effect was statistically significant at the 5% level. The likely explanation for this outcome is that customary land tenure does not provide sufficient security for long-term investments, such as adopting agricultural technologies, nor does it grant farmers the flexibility to access financial resources like loans. In contrast, farmers with non-customary land tenure have greater security and financial access, which may have encouraged them to adopt blockchain technology. Additionally, customary land is often fragmented due to subdivisions among family members over generations, further limiting its suitability for investment in modern technologies. This finding aligns with Toader *et al*. (2024) who argued that farmers with customary land tenure often lack land titles to use as collateral for agricultural credit.

The distance (in kilometres) from the household/ barley farm (wherever post-harvest handling activities like drying took place) to Company B buying centres was negative and significant at a 5% level with the adoption of blockchain. A 1 KM increase in distance decreased a barley farmer's probability of adopting blockchain by 4.5%. One explanation for this could be that once a farmer decides to adopt blockchain, inputs such as seeds, fertilizers, insecticides, herbicides, drying materials, and packing supplies are expected to be obtained from Company B buying centres. In a similar vein, the output was to be supplied directly to Company B's buying canters, with payment for it to follow. In this case, an additional kilometre would mean that farmers would need to travel unfavourable longer distances to obtain inputs and deliver their produce. Over time, this would raise transaction costs, which would lower the likelihood of adoption. This result, which considered Company B as a potential input market, is consistent with Li *et al*. (2024), who noted that farmers located far from input markets typically face higher costs for obtaining necessary production and marketing inputs.

The variable, size of land owned by a farmer, had a positive and significant effect on adoption of blockchain technology at a 5% level of significance, implying that an extra acre of land owned by a farmer increased the likelihood of adopting blockchain by 11.2%. Land is a valuable resource in smallholder farming communities because it affects the level of production. Thus, ownership of large land landholdings by barley farmers is associated with higher financial resources, better access to agricultural inputs, and a higher capacity for investment in cutting-edge technologies like blockchain. As a result, farmers who own larger tracts of land were more likely to dedicate large portions of their land to barley farming and adopt blockchain to leverage its benefits. Similar findings were reported by Temesgen and Aweke (2023) and Emran *et al*. (2021), who found a positive influence of size of land owned with adoption of agricultural technologies.

Relating to the initial cost of blockchain, the results found a negative and significant, effect on the adoption of blockchain at 1% level, The likelihood of adoption was reduced by 0.2% with a unit increase (in USD) of the initial cost of blockchain. In a smallholder farming context, like the current study situation, the negative and significant effect of the initial cost of blockchain on its adoption likely reflects the financial limitations faced by these farmers. Smallholder farmers often operate with minimal capital and have limited access to credit, making it difficult for them to afford high upfront costs associated with adopting new technologies like blockchain. Even a small increase in the cost could discourage adoption, as farmers prioritize essential expenses such as seeds, fertilizers, and labour. The finding aligns with recent studies by Masi *et al*. (2022) and Mishrif and Khan (2023), which show that high initial costs of blockchain technologies, like precision agriculture, deter smaller farms and firms due to limited financial resources and credit access.

The adoption of blockchain technology was positively and significantly affected by its compatibility with farmers' mobile phones. This relationship was significant at the 1% level of significance. This suggested that adoption would rise by 10.4% if the blockchain software app was compatible with a farmer's phone. This blockchain technology compatibility, for smallholder farmers and agribusinesses, could have meant a smoother and more affordable transition. This result is consistent with Choi *et al*. (2020), who found that technological compatibility with existing computers, systems, and mobile devices not only lessens resistance but also enhances adoption of some blockchain technologies by reducing the need for major infrastructure changes. Ullah *et al*. (2021) substantiate the results of this study by pointing out that farmers could take advantage of blockchain's capabilities for improved data accuracy and real-time decision-making without having to replace their entire tech ecosystem, which would require them to buy new mobile devices. Compatibility is typically used to proxy technology interoperability (how well a technology works with existing devices).

Marketing costs had a negative but significant effect on the adoption of blockchain, at the 5% level of significance, implying that a unit increase (in USD) in the cost of marketing significantly reduced the adoption probability by 1.3%. The costs associated with marketing comprised transportation to Company B buying centres and drying grounds, costs for drying and packing materials, and expenses for obtaining pricing information. One possible reason for this negative relationship is that farmers thought it would be more costly to transport their barley to the Company B buying centres rather than conventional ways of selling to middlemen. Due to the study area's poor road conditions and high topography, donkeys and motorcycles were the most popular forms of transportation; trucks were only used during dry days. Although output transportation proved to be costly, blockchain enabled payments to barley farmers were only possible at the buying centres. With all these factors at a play, blockchain adoption was greatly hampered by increased marketing costs. Ugochukwu and Phillips (2018) found similar results, showing that higher marketing costs increase farmers' risk and uncertainty, further discouraging adoption due to concerns about return on investment.

The possession of mobile phones by farmers had a positive and highly significant relationship with BCT adoption at a 1% level of significance. A farmer owning a phone increased the probability of adopting BCT by 14.2%. Possession of mobile phones facilitated the exchange of farming information and big data across the actors in the barley value chain which could have encouraged the barley farmers to adopt blockchain technology. This aligns with Khan *et al*.'s (2022) findings on Indian agriculture and Akella *et al*.'s (2023) finding that mobile phones support blockchain platforms adoption among smallholder farmers by enabling the storage and processing of immutable transactions.

### 4.3.4 Factors affecting extent of adoption of blockchain technology among barley farmers in eastern Uganda

The second hurdle which was modelled by the censored Tobit regression model indicates the results of the factors affecting the extent of use of blockchain, and are presented in Table 4.35.

**Table 4.35:** Factors affecting the extent of use of blockchain technology

| Variable | Coefficients | Standard error | p-value (P>z) |
|---|---|---|---|
| Sex (1=Male, 0=Female) | 0.2496727 | 0.1359413 | 0.077* |
| Age of the respondent (years) | 0.0114795 | 0.0038683 | 0.003*** |
| Education level (years in school) | 0.0235857 | 0.0105765 | 0.067** |
| Marital status (1=Married, 0=single/widowed) | 0.2651991 | 0.2076421 | 0.202 |
| Extension services (Frequency of visits) | 0.0579478 | 0.0355427 | 0.103 |
| BCT training (number of visits) | 0.1852887 | 0.043439 | 0.000*** |
| BCT training cost (USD) | 0.0000518 | 7.47e-06 | 0.000*** |
| Group membership (1=Yes, 0=Otherwise) | 0.2141277 | 0.0794843 | 0.007*** |
| Network stability (1=Stable, 0=Otherwise) | 0.0838428 | 0.0980736 | 0.393 |
| Production costs (USD) | -9.30e-08 | 9.50e-08 | 0.328 |
| Power connectivity | 0.1608215 | 0.1372075 | 0.241 |
| Land tenure | 0.0721947 | .075692 | 0.340 |
| Distance to Company B buying centre (KM) | -0.0239299 | 0.0114044 | 0.036** |
| Land size owned by a respondent (Acres) | -0.0389275 | 0.0178605 | 0.029** |
| Initial cost of BCT app (USD) | -0.0005889 | .0002712 | 0.030** |
| Costs of extension (USD) | 6.14e-07 | 0.0000127 | 0.727 |
| Marketing costs (USD) | 1.91e-07 | 5.47e-07 | 0.528 |

| | | | |
|---|---|---|---|
| Phone ownership (1=Yes, 0=Otherwise) | -0.2458692 | 0.2718416 | 0.366 |
| Constant | 2.663543 | 0.4159353 | 0.000*** |
| Sigma Constant | 0.5552063 | 0.0250894 | 0.000*** |
| Observations | 490 | | |
| Wald $Chi^2(19)$ | 14928.24 | | |
| Prob>$Chi^2$ | 0.0000 | | |
| Log pseudolikelihood | -202.65155 | | |

Note: ***, **, * denote significance level at 1%, 5%, and 10% levels respectively

1 USD = Ugx 3,682/= as of 2025

Sex of the respondent was found to have a significantly positive effect (at a 10% level of significance) on the extent of use of blockchain in the barley value chain, with a farmer being male increasing the extent of use by 24.9%. Male headed households are perceived to have an edge than female headed households in terms of ownership of resources such as land (size of land) and financial resources which would enable them to continuously use blockchain in their barley value chain activities. This result is consistent with that of Neway and Zegeye (2022), who found that households headed by women adopted agricultural technologies at lower extents because they had less access to land, education, and other resources for production. Furthermore, a male's ability to easily manoeuvre bicycles and motorbikes allowed for a greater extent of blockchain utilization than that of female respondents, as the majority of transactions involved interactions between the farmer and Company B buying centers (Azumah *et al*., 2023).

The age of the respondent had a positive and significant effect at a 1% level of significance with the extent of use of blockchain, with each additional year of a farmer increasing the extent of use by 1.1%. Old age, among farmers in smallholder farming communities like Eastern Uganda, is usually associated with more experience and a deeper understanding of farming practices which increases their extent of using agricultural technologies like blockchain. Owing to this, older farmers can assess the longer-term effects of new technologies, and have accumulated resources to enable their adoption thus incorporating them in their value chain activities extensively, consistent with the findings of Boufous *et al*. (2023).

Education level was another variable with a significant positive effect on the extent of use of blockchain by barley farmers at a 10% level. The implication here is that an increase by one year in school increased the extent of use of blockchain technology by 2.4%. This might have been the case because, farmers with higher levels of education are more likely to use blockchain frequently since they are better able to comprehend its intricate processes and see its potential benefits like transparency, traceability, and trust in the barley value chain. Studies by Sendros *et al*. (2022) and Krithika and Zareena (2022), also indicate similar results to this study's findings. Additionally, Natraj *et al*. (2024) also stresses that blockchain requires a certain level of knowledge, and farmers with higher education are better equipped to navigate the complexities associated with understanding the underlying benefits, such as data management, farmers' record keeping, elimination of middle men, and coordination of the barley value chain. This educational advantage enables these barley farmers to use blockchain more frequently and extensively so as to leverage its benefits.

Tailored training in blockchain was represented by the number of contact visits a farmer had with Company B field staffs, and this was positive and significantly affected the extent of use of blockchain by barley farmers at a 1% level of significance. Extra contact with Company B staffs training on blockchain technology by one time increased the number of seasons farmers used blockchain in the barley value chain activities by 18.5%. This was attributable to the notion that during the frequent trainings, farmers were furnished with tailored knowledge on blockchain which enhanced their perception of the technology, thus frequency of use season after the other. This finding agrees with that of Panwar *et al*. (2023) that tailored training allows users to understand the applicability and usefulness of blockchain technology platforms which, in turn, encourages more frequent and extensive use.

In the same vein, the cost of blockchain-tailored training had a positive and significant effect on the extent of use of blockchain, and this relationship was significant at a 1% level of significance. This means that even with the extra increase in the cost of accessing blockchain-tailored training by 1 USD, the extent of use of blockchain technology increased by 0.005%. This result underlines a positive inclination of farmers regarding the continued use of blockchain. This might be explained by the technology's apparent benefits to the barley value chain such as farmer information security and unique farmer identities that guaranteed economic history, which is line with the findings of Capetillo *et al*. (2022). This result, however, differs from previous research by Vern *et al*. (2023), which found that although blockchain has many advantages, its widespread adoption in agriculture may be hampered by its high implementation costs, which include training costs, especially in resource-poor areas like eastern Uganda.

Membership to farmer groups was found to have a positive and significant effect, on the extent of use of blockchain technology at a 1% level of significance. A farmer belonging to a group increased the usage extent by 21.4%. Group membership was expected a priori to have a positive effect on the extent of use of blockchain technology basing on the notion that through groups, barley farmers were able to share farming information and brainstorm on possible ways of improving the farming outcomes including use of agricultural technologies like blockchain. This result aligns with the argument made by Nandhini *et al*. (2023) that that group participation considerably raises the extent of blockchain use, which boosts farm revenues.

Distance to Company B buying centre (in kilometres) was represented by the distance from the point where transportation of barley output to the buying centre started. This could have been a household or the farm if the drying ground was at the farm. This distance was negatively related with the extent of usage of blockchain at a 5% level of significance. This implies that an increase in the distance by 1 kilometre, reduced the usage extent by 2.4%. The distance to Company B buying centres has a direct effect on the transport costs incurred by the farmers for barley to reach the buying centres; the longer the distance, the more the transport costs, and the less likely the farmer will continue using blockchain technology in the proceeding seasons. The current findings concur with those of Demestichas *et al*. (2020) that the extensive use of blockchain in agriculture is significantly hampered by geographic and infrastructural factors, making it less frequently adopted by farmers in remote locations.

The size of land owned by the farmers had a negative significant effect on the extent of adopting blockchain technology by farmers, and this was at a 5% significance level. An extra acre of land owned by a farmer reduced the number of seasons a farmer would use blockchain in the barley value chain by 3.8%. It is conceivable that farmers with larger plots of land would decide not to plant barley in the following seasons and instead experiment with other crops that compete with barley, such as onions and Irish potatoes. This was a common practice among farmers with big patches of land as they preferred to crop rotate for soil conservation purposes rather than practicing monoculture. As a result, the next season's plant would not be barley and thus the inability to use blockchain season after season, reducing the extent of use. Butkevičienė *et al*. (2021) also observed that multi-year crop rotations are a more profitable option for large-scale farms due to their ability to increase yields, improve weed suppression, and decrease the demand for synthetic inputs. Crop rotation is appealing to farmers with large land areas since it enables varied revenue streams from numerous crops, as noted by Jourdain *et al*. (2020).

The initial cost, to the farmer, of acquiring blockchain was observed to have a negative significant effect on the extent of use of blockchain technology. This relationship was significant at the 5% level of significance with an increase in the initial cost by a unit of USD reducing the extent of use by 0.05%. Similar to the priori expectation, this finding indicates that farmers were not inclined to continue using blockchain due to its associated high costs, which in turn reduced the extent of use. Costs of acquiring and incorporating disruptive technologies like blockchain in the smallholder farmers' crop value chains have been observed by Akella *et al*. (2023) to reduce their widespread use. This is because smallholder farmers usually face challenges of accessing affordable financing options.

### 4.4 Effect of blockchain technology on barley productivity and farmers' gross margin

This section examines the effect of blockchain technology on barley productivity and farmers' gross margins, highlighting how its adoption or non-adoption influences yield outcomes and financial performance.

#### 4.4.1 Productivity analysis

The analysis of productivity was done to provide insights into and account for the differences and similarities among the blockchain technology adopters and non-adopters, as presented in Table 4.36**.**

**Table 4.36:** Barley productivity analysis

| | BCT adopters (N=245) | | BCT non-adopters(N=246) | | |
|---|---|---|---|---|---|
| Variable | Mean | Std.dev | Mean | Std.dev | *t*-test |
| Barley output (Kg/acre) | 1569.796 | 998.978 | 1226.89 | 936.952 | 3.923*** |
| Seed quantity planted (Kg/acre) | 52.989 | 17.630 | 45.707 | 14.628 | 4.410*** |
| Fertilizer quantity used (Kgs/acre) | 44.162 | 20.710 | 20.873 | 17.809 | 13.361*** |
| Labour (man per day per acre) | 15 | 11 | 15 | 8 | 0.5449 |
| Household labour (Active adults) | 4 | 2 | 3 | 2 | 3.216*** |
| Productivity (output/acre) | 1287.721 | 348.772 | 1041.825 | 398.197 | 7.278*** |

Note: *, ** and *** denotes = significant at 10%, 5% and 1% level, respectively

All the variables used in the analysis of barley productivity, except labour, showed positive and significant differences between blockchain technology adopters and non-adopters, with adopters displaying higher average values. The mean differences were statistically significant at the 1% level. For barley output, adopters had a mean yield of 1569.8 kg compared to 1226.9 kg for non-adopters, suggesting adopters achieved higher yields. This difference likely came from timely farming, access to better inputs, which were made possible through blockchain technology. Adopters also used more seeds and fertilizers, 52.99 kg and 44.16 kg, respectively, likely attributed to payment waivers on inputs, not available to non-adopters. The mean household labour engaged in production was 4 members for blockchain adopters and 3 for non-adopters, indicating higher labour input among adopters. Overall mean productivity per acre also differed, with adopters obtaining 1287.72 kg per acre compared to 1041.83 kg per acre for non-adopters, suggesting that blockchain technology adoption contributed to increased barley productivity. These findings concur with prior studies showing that blockchain-enabled technologies boost productivity across agricultural value chains, such as in Tsang *et al*. (2019).

#### 4.4.2 Gross margin analysis

Gross margin, a second measure of performance, was analysed to provide insights into the differences or similarities among the two farmer groups. the results are presented in Table 4.37.

**Table 4.37**: Gross margin analysis

| | **BCT adopters (N=245)** | | **BCT non-adopters(N=246)** | | |
|---|---|---|---|---|---|
| **Variable** | **Mean** | **Std.dev** | **Mean** | **Std.dev** | ***t*-test** |
| Barley quantity sold (Kgs/acre) | 1187.374 | 318.523 | 747.5 | 330.157 | 15.023*** |
| Price (USD/Kg) | 0.41 | 0.087 | 0.37 | 0.030 | 22.831*** |
| Cost of seeds (USD/acre) | 14.90 | 13.27 | 18.95 | 0.0044 | -3.033*** |
| Cost of fertilizers (USD/acre) | 0.012 | 0.0058 | 0.0059 | 18.38 | 13.361*** |
| Cost of human labour (USD/acre) | 30.56 | 2.26 | 31.51 | 15.61 | -0.5449 |
| Other costs overall (USD/acre) | 85.04 | 35.31 | 84.57 | 43.34 | 0.129 |
| Total variable costs (USD/acre) | 195.36 | 60.81 | 171.43 | 63.00 | 4.282*** |
| Total revenue (USD/acre) | 491.73 | 131.57 | 286.98 | 187.13 | 14.020*** |
| **Gross margin (USD/acre)** | 296.37 | 120.41 | 115.54 | 176.20 | 13.271*** |
| **Profitability ratio (%/acre)** | 59.309 | 33.2744 | 30.267 | 3.137 | 7.659*** |

Note: *, ** and *** denotes = significant at 10%, 5% and 1% level, respectively

1 USD = Ugx 3,682/= as of 2025

With the exception of labour expenses and other overall expenditures, all gross margin analysis factors exhibit significant mean variances at the 1% level. The estimates are calculated on an acre-by-acre basis. The mean quantity of barley sold per acre was 1187.374 kg for blockchain adopters and 747.5 kg for non-adopters. This suggests that blockchain adopters sold more barley than non-adopters, most likely as a result of their increased yield and improved postharvest handling techniques, like appropriate drying. Adopters sold at higher prices than non-adopters, with the mean price for blockchain adopters being USD 0.41 versus USD 0.37 for non-adopters. This might be because Company B offered adopters better prices than non-adopters, who mostly sold to middlemen at cheaper prices, and because blockchain technology benefits from pricing transparency. Tian (2017) similarly noted that blockchain technology increases pricing systems' transparency for all stakeholders involved in the value chain.

The average seed and labour costs per acre were significantly lower for blockchain adopters (USD 14.90 for seeds) than for non-adopters (USD 18.95), indicating that non-adopters generally paid higher prices for inputs. This may be due to purchasing from more expensive agro-input dealers or markets. Non-adopters faced greater information asymmetry around input prices, leading to higher expenses, while BCT adopters benefited from transparent pricing at Company B buying centres. This is consistent with findings by Kraft and Kellner (2022), who noted that blockchain improved information transparency within the Ghanaian cocoa supply chain, reducing farmer exploitation. The average labour cost per acre was lower for blockchain adopters (USD 30.56) than for non-adopters (USD 31.51), possibly due to adopters utilizing machinery or animal labour, which reduced their reliance on human labour. In contrast, adopters spent significantly more on fertilizers, with a mean of USD 45.58 compared to USD 21.54 for non-adopters. This suggests that blockchain adopters used higher quantities of fertilizer, driving up their costs but potentially contributing to higher yields

The mean total variable costs per acre were higher for blockchain technology adopters (USD 195.36) than non-adopters (USD 171.43), largely due to the proportion of other costs including herbicides, pesticides, fungicides, transport, drying, and packaging. This increased spending aligns with the higher production levels of blockchain adopters, as variable costs generally rise with increased output (Pamukova & Momchilov, 2017). On the other hand, blockchain adopters had a significantly higher mean revenue per acre (USD 491.73) than non-adopters (USD 286.98), possibly driven by greater output, better quality of produce, and better prices. This led to a larger average gross margin for adopters (USD 296.37) versus non-adopters (USD 176.20), attributable to lower transaction costs, more transparent pricing, and information symmetry. Consequently, adopters' mean profitability ratio per acre (59.3%) outpaced that of non-adopters (30.3%), likely due to their effective use of blockchain technology advantages and better farm management practices (Panwar *et al*., 2023).

### 4.4.3 Effect of blockchain technology on the performance of barley farmers

The results of the effect of blockchain technology on the performance of barley farmers are presented in Table 4.38**.** Performance was measured by using barley productivity (natural log of productivity) and gross margin (natural log of gross margin), and the results presented are from the Full Information Maximum Likelihood (FIML) of Endogenous switching regression model (ESR) as well as the average treatment effects on the treated (ATT) and average treatment effects on the untreated (ATU). The treated farmers were those that choose to adopt blockchain while the untreated farmers are those that choose not to adopt blockchain technology.

### 4.4.4 Model diagnostic tests

The diagnostic tests were assessed for both the outcome equations of barley productivity and farmers' gross margin

**The outcome equation of barley productivity:** Firstly, the FIML estimation was done on barley productivity as a measure of performance. ESR model estimated both the selection and the productivity equations simultaneously. The model diagnostic tests included falsification test on the selected instruments, likelihood ratio test for joint independence, and the Wald test. The results of the falsification test showed that the instruments chosen, group membership (Yes=1, No=0) and received blockchain tailored training (Yes=1, No=0), were individually influencing the blockchain technology adoption decision equation but jointly did not significantly affect productivity equation (F2=230, p-value=0.2796). Because the chosen instruments had no direct impact on barley productivity, they were appropriate for determining the regime equations. The Wald Chi-Square test statistic was used to test the overall significance of the explanatory variables in the model. With the degrees of freedom distributed at 13 (13 independent variables were included in the model), the value obtained (Wald $\chi^2(13)$ =44.33, p-value=0.0000) indicated that at least some of the explanatory variables were significant in explaining the variability in productivity. The highly significant p-value indicated that overall, the explanatory variables in the model jointly had a statistically significant effect on productivity. Taking the absolute value of the log likelihood value (-334.38), it was deduced that the model fitted well the data, since this measure alone may not satisfy model fit analysis unless compared with other measures.

**The outcome equation of farmers' gross margin:** Secondly, the FIML estimation was modelled with farmers' gross margin as a measure of performance, with ESR estimating both the selection and the regime (gross margin) equations simultaneously. In the model diagnostic test, falsification test results indicated that instruments selected, that is, received blockchain tailored training (Yes=1, No=0) and distance to Company B buying centre (walking minutes) were jointly not significant (F2=234, p-value=0.9275) in affecting the gross margin equation but were individually affecting blockchain adoption decision equation. Thus, the selected instruments were suitable for identifying the regime equations since they did not affect farmers' gross margin directly. This Likelihood Ratio (LR) test examined whether the two equations in the ESR model were independent, and it is based on the null hypothesis that the error terms of the two equations (the selection equation and the gross margin equation) are uncorrelated (i.e., there is no endogenous switching). The $chi^2(1)$ statistic tested the null hypothesis of independence with 1 degree of freedom. From the results, a $chi^2$ value of 9.85, with a p-value of 0.0017 was obtained, indicating that the null hypothesis of independent equations was rejected. This implied that the error terms of the two equations were correlated, hence there was indeed endogenous switching and that the model correctly accounted for it.

The Wald test statistic is based on the null hypothesis that all of the coefficients in the model (except the intercept) are simultaneously equal to zero. From the results, $\chi^2(9)$ =238.87 was large suggesting that at least one of the coefficients (out of the nine, $\chi^2(9)$, explanatory variables tested in the model, except the intercept) was significantly different from zero. The p>0.0000 confirms that the null hypothesis was rejected at 1% confidence level, thus the model as a whole was statistically significant. The results on the log likelihood = -537.57622 indicated that the model fitted the data well, taking into consideration the absolute value of the log-likelihood.

**Table 4.38:** FIML estimation results of ESR for the selection and outcome equation

| | Selection and productivity equations | | | Selection and gross margin equations | | |
|---|---|---|---|---|---|---|
| | | BCT adopters=1 | BCT non-adopter=0 | | BCT adopters=1 | BCT non-adopter=0 |
| Explanatory variable | Selection equation (1) | Log of productivity per acre (2) | Log of productivity per acre (3) | Selection equation (4) | Log of gross margin (5) | Log of gross margin (6) |
| Age of the respondent | -0.0258*** | 0.0028 | -0.0033 | 0.0056 | 0.0001 | -0.0015 |
| | (0.0091) | (0.0027) | (0.0028) | (0.0058) | (0.0018 | (.0036) |
| Sex of the respondent (Male=1, Female=0) | 0.3981 | -0.1553** | -0.0492 | 0.3569* | -0.1098* | -0.0412 |
| | (0.2502) | (0.0637) | (0.0912) | (0.2126) | (0.0616) | (0.1553) |
| Barley farm size (acres) | | | | 0.0218 | 0.4102*** | 0.2601*** |
| | | | | (0.0838) | (0.0291) | (0.0475) |
| Main occupation of the household | 0.8607*** | -0.0081 | -0.0190 | 0.6186** | 0.1667* | -0.0376 |
| | (0.3024) | (0.0995) | (0.0945) | (0.2673) | (0.0988) | (0.1582) |
| Group membership (Yes=1, No=0) | 0.6957*** | | | 1.0361*** | 0.1119** | -0.1804* |
| | (0.1503) | | | (0.1332) | (0.0502) | (0.1021) |
| Extension services received | | | | 0.0354 | -0.0616 | 0.1951** |
| | | | | (0.1541) | (0.0490) | (0.0971) |
| Network stability | | | | -0.0049 | 0.0032 | -0.1027 |
| | | | | (0.1680) | (.0528) | (0.1060) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Credit access | | | | -0.7520*** | -0.0992** | -0.1874** |
| | | | | (0.1335) | (0.0473) | (0.0936) |
| Log of total annual non-barley income | | | | 0.1539* | -0.0631** | 0.1202** |
| (USD) | | | | (0.0872) | (0.0285) | (0.0528) |
| Quantity of seeds planted per acre (Kgs) | 0.0148*** | 0.0011 | 0.0097*** | | | |
| | (0.0049) | (0.0013) | (0.0017) | | | |
| Quantity of fertilizer used per acre (Kgs) | 0.0424*** | -0.0006 | 0.0004 | | | |
| | (0.0042) | (0.0012) | (0.0019) | | | |
| Labour (man per acre per season) | -0.0240*** | 0.0017 | 0.0067** | | | |
| | (0.0075) | (0.0021) | (0.0033) | | | |
| Barley farming experience (Years) | 0.0983*** | -0.0301*** | -0.0244*** | | | |
| | (0.0241) | (0.0070) | (0.0092) | | | |
| Household labour (No. of adult household | 0.1611*** | 0.0194 | -0.0003 | | | |
| members capable of production) | (0.0491) | (0.0131) | (0.0171) | | | |
| Land Tenure (Customary=1, Non- | -0.2940* | -0.0074 | 0.1948*** | | | |
| customary/Commercial =0) | (0.1517) | (0.0432) | (0.0502) | | | |
| Size of land owned (acres) | 0.0579 | -0.0182* | 0.0072 | | | |
| | (0.0385) | (0.0102) | (0.0131) | | | |
| Education level (No. of years in school) | 0.0398* | -0.0049 | -0.0222*** | | | |
| | (0.0208) | (0.0062) | (0.0076 | | | |
| Log of Distance to Company B buying | -0.3945*** | 0.1037*** | 0.1352*** | | | |
| centres (Walking minutes) | (0.0860) | (0.0251) | (0.0342) | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| Distance to barley farm (walking minutes) | 0.0106 | -0.0008 | -0.0097** | | | |
| | (0.0125) | (0.0035) | (0.0041) | | | |
| BCT tailored training | 0.5191*** | | | | | |
| | (0.1851) | | | | | |
| Distance to Company B buying centres (Walking Minutes) | | | | | | |
| Constant | -2.5269*** | 6.9589*** | 6.1678*** | -3.6642*** | 14.5686*** | 12.1154*** |
| | (0.7350) | (0.2164) | (0.2423) | (1.2671) | (0.4246) | (0.7334) |
| Sigma (standard deviations of error terms, $\sigma_1$ and $\sigma_2$) | | 0.3290 | 0.3678 | | 0.3156 | 0.6240 |
| | | (0.0199) | (0.0190) | | (0.0199) | (0.0282) |
| rho (correlation of error terms between selection and regime equations ($\rho_1$ and $\rho_2$) | | -0.7516*** | -0.3461* | | 0.5581*** | -0.0370 |
| | | (0.1135) | (0.1787) | | (0.1196) | (0.1734) |
| | | Number of observations = 491 | | | Number of observations = 491 | |
| | | Log likelihood = -334.38282 | | | Log likelihood = -537.57622 | |
| | | Wald chi2(13) = 44.33 | | | Wald chi2(9) = 238.87 | |
| | | Prob > chi2 = 0.0000 | | | Prob > chi2 = 0.0000 | |
| | | LR test of indep. eqns chi2(1) = 6.92 | | | LR test of indep. eqns chi2(1) = 9.85 | |
| | | Prob > chi2 = 0.0085*** | | | Prob > chi2 = 0.0017*** | |

**Note:** *, ** and *** denotes = significant at 10%, 5% and 1% level, respectively, figures in parentheses are standard errors.

1 USD = Ugx 3,682/= as of 2025

### 4.4.5 Endogeneity in the relationship between the selection and regime equation outcomes

To gain insights into the relationship between the selection mechanism of blockchain technology and the productivity variable in two different regimes (adopters and non-adopters), ESR results on the two regimes were presented in Table 4.38 (last 2 bottom rows). In regime 1, the model results revealed a strong and statistically significant negative correlation, at 1% level, between the unobserved variables affecting the decision to adopt blockchain technology (selection into regime 1) and the productivity in regime 1 ($\rho_1$=−0.752), indicating potential adverse selection. The variability (standard deviation) of unobserved variables in regime 1 was moderate ($\sigma_1$=0.329). In regime 2, there was a weak negative but statistically significant, at 10% level, correlation between selection into regime 2 (BCT non-adopting decision) and productivity in regime 2 ($\rho_2$=−0.346), suggesting that unobservable variables that influence selection into regime 2 had little impact on productivity. The variability (standard deviation) of unobserved variables in regime 2 was somewhat higher (σ2=0.368). Regarding endogeneity, the Log likelihood ratio ration (LR) test of independent equations result confirmed that the selection and outcome equations were not independent ($\chi^2(1)$ = 6.96, p-value = 0.0083), underscoring the importance of using an endogenous switching regression model to account for selection bias.

Regarding gross margin, the results of the ESR further provided insights into the relationship between the BCT selection mechanism and the gross margin variable in two different regimes. The standard deviations of the error terms in each regime were statistically significant at 1% level ($\sigma_1$ =0.3156, p=0.000 and $\sigma_2$=0.6240, p=0.000), indicating greater unobservable variability in the second regime (with higher deviation, $\sigma_2$=0.6240) compared to the first ($\sigma_1$ =0.3156). This confirmed the presence of endogeneity problem. Further, the correlation coefficient $\rho_1$=0.5581 was significantly positive (p=0.000), suggesting that unobservable variables driving selection (BCT adoption decision) into the first regime were positively correlated with unobservable variables that affected gross margin in this regime. This implies that individuals selected into the first regime (farmers that chose to adopt BCT) may have had characteristics that also enhanced gross margin.

In contrast, the correlation coefficient for the second regime, $\rho_2$=−0.0370 was small and statistically insignificant, suggesting that the selection process in the second regime did not correlate meaningfully with gross margin. This could indicate that the unobserved factors driving selection into the second regime did not systematically affect gross margin variable in the same way. These findings highlight the importance of accounting for endogenous switching in this context, particularly for the first regime, where selection and outcomes were correlated.

#### 4.4.6 Determinants of blockchain technology adoption decision in the two selection equations

From the Table 4.38, columns (1 and 4), display the estimated coefficients from the blockchain technology selection equations of both productivity and gross margin outcomes. The adoption of blockchain was negatively and significantly dependent on age, whereby as farmers advanced in age, they were less likely to adopt blockchain compared to younger ones. This is likely due to older farmers being more risk-averse, less inclined toward innovation, and less entrepreneurial (Okello, 2017). The results further indicated that the sex of the respondent significantly influenced the decision to adopt blockchain, with male farmers more likely to adopt than female farmers. This disparity could be attributed to differences in resource access, decision-making, and social networks, where male respondents generally performed better. Additionally, gender-specific roles, such as the ability to access Company B buying centres via motorbikes, further favoured males in adoption of blockchain. This aligns with findings from Radović-Marković *et al*. (2020), which showed that women farmers in Bangladesh have lower adoption rates of modern agricultural technologies.

The main occupation of respondents had a positive and significant effect on the decision to adopt blockchain technology, at 1% and 5% levels, under the productivity and gross margin outcome equations respectively. Respondents whose main occupation was farming including barley farming were highly likely to adopt blockchain technology compared to those whose main occupation was non- farming activities. This is credible, because respondents primarily engaged in farming may perceive blockchain as a tool for enhancing barley value chain transparency, which could help secure better prices and higher returns, which could make them more inclined to adopt it. This finding is supported by Mottaleb's (2018) study, who found that a farmer's primary occupation in farming positively influenced their adoption of new irrigation technologies in Bangladesh.

Similarly, group membership significantly influenced the decision to adopt blockchain technology, demonstrating a positive and significant effect in both productivity and gross margin outcome equations at a 1% significance level. Being part of a group enables farmers to exchange experiences, share information, and acquire knowledge about new technologies, thereby enhancing their likelihood of adopting blockchain technology. This collaborative environment fosters a sense of community and trust, which is crucial for encouraging innovation in agricultural practices. Research by Nandhini *et al*. (2023) supports this notion, indicating that participation in farmer groups facilitates the dissemination of information regarding blockchain, ultimately promoting its adoption.

Under the gross margin outcome equation, the need for credit negatively affected the adoption of blockchain technology, with a significant effect at the 1% level, implying that farmers requiring more credit were 75% less likely to adopt blockchain technology. The dire need for credit among farmers highlights their financial constraints, which hinder technology adoption. The financial constraints may push farmers toward multiple borrowing practices that may lead to side-selling barley instead of entering blockchain contracts with Company B. Conversely, farmers with additional non-barley income were more inclined to adopt BCT as their incomes rose, supporting Dong *et al*. (2024) in highlighting the importance of financial flexibility for adopting agricultural technologies. Such financial flexibility provides farmers with confidence and a safety net to mitigate the risks associated with new technology adoption.

Under the productivity outcome equation, the quantity of seeds planted per acre was positively and significantly related with blockchain adoption decision, at a 1% level of significance. This implies that the increase in the quantity of seeds planted by 1 kg increased the likelihood of adopting blockchain technology by 1.4%. Given that seeds are one of the essential inputs in barley production, farmers might have been drawn to adopt blockchain technology as it enabled them to receive the seeds as advance from Company B, even without cash payments. This access to inputs through blockchain likely made the technology more appealing, as it offered farmers practical, immediate benefits in managing production costs and ensuring timely resources. Similar findings were observed by Goyal *et al*. (2022), indicating that blockchain technology facilitates the distribution of inputs in a manner that minimizes financial risks for farmers.

Correspondingly, the quantity of fertilizers used per acre in barley production was found to have a positive and statistically significant relationship with the decision to adopt blockchain technology at the 1% significance level. Specifically, a 1 kg increase in fertilizer usage corresponded to a 4.2% rise in the likelihood of adopting blockchain. Fertilizers are crucial for enhancing crop yields by supplying essential nutrients. Farmers may be incentivized to adopt blockchain technology because it allows them to obtain the required fertilizers for their barley fields as advances from Company B without upfront cash payments. This mechanism facilitates access to fertilizers, which might otherwise be prohibitively expensive and challenging to procure, making blockchain technology more attractive by offering practical, immediate benefits in managing production costs and ensuring timely resource availability. This finding is consistent with Ahmed *et al*. (2020) who reported that blockchain technology enables transparent and efficient distribution of fertilizers among Indian smallholder farmers at fair prices.

Labor, measured as the number of men providing labour per day per acre was shown to have a negative and statistically significant impact on the decision to adopt blockchain technology, at the 10% level. Specifically, a reduction of one man per acre per season led to a 2.4% decrease in the likelihood of adopting blockchain technology. This may be attributed to the high costs associated with labour and the financial constraints faced by farmers, prompting them to seek advance cash from middlemen to hire additional labour instead of adopting blockchain technology, which primarily offers advances in seeds and agrochemicals. Conversely, the availability of household labour had a positive and significant effect on the likelihood of adopting blockchain technology, increasing it by 16.1%. Households with more adult and active members in the production cycle encountered fewer labour challenges, making them more inclined to adopt blockchain and benefit from its offerings of seeds, agrochemicals, enhanced transparency, and better pricing. This finding aligns with Alobid *et al*. (2022), who noted that greater labour availability positively influences the adoption of innovative technologies and practices in agriculture.

Regarding experience in barley farming, each additional year of experience increased the likelihood of adopting blockchain by 9.83%, with significance at the 1% level. Experienced farmers likely benefitted from practical insights that highlight technology's value for productivity and resource management, and they could better assess associated risks. Similarly, a Ugandan study by Ainembabazi and Mugisha (2014) confirmed a positive relationship between farming experience and technology adoption. Contrariwise, land tenure had a negative effect on blockchain adoption, as farmers with customary land ownership were less likely to adopt blockchain than those with commercial land ownership. This may be due to the restrictions under customary systems, which limit farmers’ autonomy for long-term investments. Diendéré and Wadio (2023) similarly found that secure land rights enhance the adoption of long-term and sustainable agricultural practices.

Education level positively and significantly influenced blockchain technology adoption decision, with more educated farmers more likely to adopt blockchain technology than the less educated ones. Education empowers farmers to make rational decisions, be innovative, and easily adjust to new technologies like blockchain technology (Manning *et al*., 2022). On the other hand, the distance to Company B's buying centres negatively affected the likelihood of adopting blockchain under both the productivity and gross margin equations. Each additional minute of walking time decreased this likelihood by 39.4%, and 0.5% respectively. This is likely because farmers frequently visited these centres for input collection and output sales. Greater distance leads to higher transportation costs, making adoption less feasible. This finding aligns with Asfaw *et al*. (2018), who noted that longer distances between farming households and input/output markets reduce the likelihood of utilizing modern agricultural inputs, such as inorganic fertilizers.

#### 4.4.7 Blockchain technology adoption decision and barley productivity outcome

From the Table 4.38, Columns (2) and (3) report on barley productivity outcomes for blockchain technology adopters and non-adopters. To ensure model identification, two probit model variables, blockchain-tailored training and group membership, were excluded from the productivity function, as tests showed they did not directly influence barley productivity. The sex of respondents negatively affected barley productivity for both adopters and non-adopters; however, the effect was significant at the 5% level only among the adopters. This implies that male adopters showed less productivity improvement from blockchain use than female adopters, indicating that gender influences productivity outcomes. This suggests that female farmers, often recognized for their dedication and resilience in agricultural activities, managed to leverage blockchain more effectively to enhance productivity. This finding aligns with a 2023 FAO report, which notes that women farmers frequently invest more effort in farm management, a factor crucial for achieving productivity gains. The FAO report further emphasizes that when women have equal access to resources as men, such as blockchain technology adoption, productivity differences narrow considerably.

The quantity of seeds planted per acre and labour input per day per acre showed positive effects on productivity among blockchain non-adopters, with significance levels of 1% and 5%, respectively. Each additional kilogram of seed and number of men per day per acre increased barley productivity by 0.9% and 0.06% respectively. This indicates that, in contrast to blockchain adopters, non-adopters, who bore full responsibility for their inputs, were likely to maximize each unit of these resources for enhanced productivity. This cost-conscious approach drove efficient resource use, aligning with Onyango *et al*. (2021), who found that optimized input management is crucial for achieving higher productivity, especially when resources are limited. Similarly, land tenure significantly impacted productivity among blockchain non-adopters, with customary landholders seeing an estimated 19.5% productivity increase. Without long-term security over land to invest in blockchain technology, non-adopters aimed to maximize productivity within each growing season on their temporarily held land. Diendéré and Wadio (2023) also observed that insecure land tenure often drives farmers toward short-term investments aimed at maximizing immediate productivity.

Interestingly, both farming experience and educational attainment were found to have significant negative effects on productivity at the 1% level. Farming experience affected productivity for both blockchain adopters and non-adopters, whereas education level showed a negative effect only among non-adopters. While studies have shown that experience and education increase productivity, the findings of this study show otherwise. Farmers with extensive experience might adhere to traditional farming practices, making them less likely improve their productivity even with the adoption of technologies like blockchain technology (Osanyinlusi & Adenegan, 2016). Equally, more educated blockchain non-adopting farmers might have diversified their focus across multiple activities or income sources rather than concentrating fully on barley farming, which could inadvertently lower barley productivity. This is similar to Mihigo's (2018) finding that higher levels of formal education could negatively affect agricultural productivity.

The log of distance to Company B buying centres positively affected productivity across the two groups, at 1% level. This result implies that each additional minute of walking time to Company B centres increased barley productivity by 10.3% for blockchain adopters and 13.5% for non-adopters. This result contrasts with the FAO's (2017) report, which suggests productivity typically improves when farmers are closer to input/output markets, in this case, Company B buying centres. However, this finding underscores the essential role of Company B's buying centres in barley production within the study area, showing that farmers were willing to travel further to access inputs, which enhanced productivity. On the contrary, increased walking time from households to barley fields lowered productivity among blockchain non-adopters. The greater distance may have limited farmers' ability to consistently supervise their farms and raised the cost of transporting inputs, ultimately leading to a decrease in productivity (Alemu *et al*., 2017).

#### 4.4.8 Blockchain technology adoption decision and farmers' gross margin outcome

The gross margin outcomes for blockchain technology adopters and non-adopters are shown in Table 4.38, Columns (5) and (6). Two variables from the probit model, the distance to Company B's buying centres and blockchain-tailored training, were removed from the gross margin equation to guarantee proper model identification because tests showed they had no direct effect on gross margin. Sex was cited to have a negative effect on blockchain adopting farmers 'gross margin, at 10% level of significance, with a farmer being male likely reducing the gross margin by 10.9%. This finding is contradicting to most studies where male farmers have been found to realize more gross margins than female farmers (Mishra *et al*., 2017;Wongnaa *et al*., 2019). The likely explanation for the present result is that male farmers sometimes exhibited a more independent and risk-oriented approach, which might have increased costs or reduced the efficacy of blockchain technology implementation for maximizing income potential.

Barley farm size had a positive and highly significant impact on gross margins for both blockchain adopters and non-adopters, with a 1% significance level. For each additional acre, gross margins rose by 41% for adopters and 26% for non-adopters, likely due to economies of scale enhancing productivity. Blockchain adopters saw further benefits, as larger farms enabled them to capitalize on transparent pricing, boosting profitability. This finding aligns with Mugera *et al*. (2016), who reported higher productivity and profitability in larger farms. Furthermore, the main occupation variable was positively significant for blockchain adopters at a 10% level, indicating that farmers fully engaged in farming increased gross margins by 16.7%. This is plausible, as these farmers view farming as their primary livelihood, and adopting blockchain enabled them to boost their gross margins through reduced transaction costs, more efficient operations, and transparent, favourable barley prices. Birthal *et al*. (2017) similarly observed efforts in India by both farmers and the government to increase farm gross margins, given farming's importance as a main livelihood source.

Group membership showed differing effects on gross margins for blockchain adopters and non-adopters. For blockchain adopters, group membership increased gross margins by 11.2% at a 5% significance level, likely due to benefits from shared information on prices and farming techniques. In contrast, non-adopters saw an 18% reduction in gross margin at a 10% significance level, possibly due to lacking these shared benefits (Ma & Abdulai, 2017). However, non-adopters' gross margins tended to improve with more frequent extension service contacts, which provided essential farming insights otherwise unavailable through blockchain. This is parallel with findings of Anang *et al*. (2020), who reported a positive link between agricultural extension services and gross margins

The need for credit had a significant negative effect on gross margins for both blockchain adopters and non-adopters at the 5% level. Non-adopters faced an 18.7% reduction, while adopters experienced a 9.9% drop, likely due to high-interest rates from informal lenders impacting overall profitability. This supports Ramprasad (2019), who highlighted the varied obligations of credit sources and their negative impacts on agriculture. Additionally, non-barley income positively affected the gross margins of non-adopters, helping them invest in barley farming (Anang *et al*., 2020; Key, 2020). For blockchain adopters, however, non-barley income had a negative effect, as higher non-barley earnings may have led them to shift focus away from barley, reducing gross margin potential, a trend also noted by Zhang *et al*. (2023b) in Chinese smallholders.

### 4.4.9 Estimation of Average Treatment Effects using the Endogenous Switching Regression

This section presents the conditional expectations, treatment effects, and heterogeneity effects derived from the endogenous switching regression analysis. These effects were analysed and discussed for both the productivity and gross margin functions as presented in Table 4.39.

**Table 4.39:** Average treatment effects of blockchain technology on barley productivity and farmers' gross margin

| | Log of barley productivity per acre | | | Log of gross margin | | |
|---|---|---|---|---|---|---|
| | Adopters (1) | Non-Adopters (2) | Treatment effect (3): ATT/ATU | Adopters (4) | Non-Adopters (5) | Treatment effect (6): ATT/ATU |
| Adopters | 7.12 | 6.75 | 0.37*** | 14.47 | 13.86 | 0.61 *** |
| Non-adopters | 7.41 | 6.87 | -0.54*** | 14.21 | 13.89 | -0.32*** |
| Heterogeneity effects | -0.29 | -0.12 | 0.91*** | 0.26 | -0.03 | 0.93*** |

***Note:*** *** denotes significance at 1% level

**Productivity function**: From the ATE estimation results presented in Table 4.39, Columns (1) to (3) it was observed that the blockchain adopting farmers obtained higher productivity of 7.12 units, compared to 6.75 units had they not adopted. Thus, blockchain adoption increased the barley productivity of blockchain adopting farmers by 0.37 units and this increment was significant at 1% level. This implies that blockchain technology increased barley productivity by 5.5%. The direct rationality here could be the advantages that were associated with adoption such as payment waivers on most essential production inputs like seeds, fertilizers and other agrochemicals (pesticides and herbicides) at the beginning of the season, but due later on delivery of output. This ensured timely operations, and the crop utilizing the early rains and escaping weed, pests and disease attacks. These, together increased productivity of a crop. The indirect explanation could be that blockchain enables smallholder farmers to gain direct access to markets, reducing the need for middlemen and ensuring they receive fairer prices for their produce. This improves profitability and incentivizes better farming practices which consequently increase productivity (Xiong *et al*., 2020). Moreover, similar results were obtained by Alobid *et al*. (2022), in their study of China's agriculture where blockchain was observed to increase productivity of smallholder farmers.

Contrary, the average treatment effect of blockchain technology on the untreated was significant at 1% level but negative. The blockchain non-adopting farmers obtained lower productivity of 6.87 units compared to 7.41 units had they adopted. Thus, the blockchain non-adopting farmers had their barley productivity reduced by 0.54 units. This translates to 7.9% reduction in barley productivity. This is logical because the non-adopting farmers were not in position to get the input payment waivers at the beginning of barley seasons as the adopters would. Coupled with the financial limitations usually associated with smallholder farmers, their access to essential production inputs was beset (Langyintuo, 2020), so was timely farming operations. Eventually, their productivity reduced, which would be reversed if they had adopted blockchain.

However, comparing the two groups, the non-adopting farmers had they adopted, would realize higher productivity (7.41 units) than that of adopting farmers whether they adopted (7.12 units) or not (6.75 units). Additionally, had both groups not adopted blockchain, the non-adopting farmers would have higher productivity (6.87 units) than the adopting farmers (6.75 units), indicating that there were other unobservable factors such as farmers' skills and attitudes towards farming that brought about the variance between the two groups. These unobservable characteristics proved the choice of ESR model to cater for endogeneity. The base heterogeneity effect of blockchain technology on barley productivity was positive and significant at 1 % level with blockchain increasing barley productivity by 0.91 units.

**Gross margin function:** Gross margin was estimated using its natural log. From the results in Table 4.39, Columns (4) to (6), adopting farmers obtained a gross margin of 14.47 units, which was higher compared to 13.86 units if they did not adopt. The value of ATT was significant and positive at 1% level with blockchain increasing gross margin by 0.61 units, which is 4.4% increase. The non-adopters on the other hand obtained a gross margin of 13.89 units, which is lower compared to 14.21 units if they adopted. The ATU value was also significant at 1% level but negative with blockchain non-adoption reducing gross margin of non-adopters by 0.32 units, which is 2.3% reduction. This outcome may be due to the advantages provided by blockchain technology, including increased transparency of market information, lower transaction costs, and enhanced pricing from Company B for farmers who adopted the technology, benefits those non-adopters lacked access to. Kumarathunga *et al*. (2022) corroborate these findings, highlighting that the advantages of blockchain contribute to improved profit margins for farmers.

Furthermore, non-adopters faced various forms of exploitation from middlemen, including receiving lower prices and experiencing significant deductions in the weight of barley sold, justified by claims of weight loss during drying. Farmers often resorted to selling undried barley to avoid drying costs and due to the lack of adequate drying facilities. Additionally, many non-adopting farmers had their barley purchased directly from the field, with middlemen estimating yields at maturity. These practices likely resulted in lower price offers for non-adopters, leading to reduced gross margins compared to their adopting counterparts.

The results further indicated that the blockchain-adopting farmers had higher gross margins (14.47 units) compared to all other scenarios: had the adopters not adopted (13.86 units), and had the non-adopters adopted (14.21 units) or not adopted (13.89 units). If non-adopting farmers had adopted, their gross margin would have increased from 13.89 units to 14.21units, though still below that of the adopting farmers (14.47 units). Again, if neither group had adopted blockchain, the non-adopting farmers would have achieved a slightly higher gross margin (13.89 units) than the adopting farmers (13.86 units), though the difference would be minimal. These findings suggest the presence of unobserved variables that created variances among farmers in the two groups, thereby justifying the use of the ESR model to correct for endogeneity.

The base heterogeneity effect value was positive and significant at 1% level indicating that adopting blockchain was associated with increasing smallholder farmers' gross margin by 0.92 units. By ensuring barley value chain transparency between the farmers and the buyers (Company B), farmers were able to sell directly to Company B at considerably higher prices compared to those offered by middlemen. In line with a priori expectation, the higher prices offered through blockchain improved gross margins of blockchain adopters.

Additionally, the farmers benefitted from secure and assured timely payments upon delivery of their produce, which reduced transaction costs and financial risks for the adopting farmers. The secure and assured transactions were attributed to blockchain enabling various payment forms to the farmers: through mobile money, bank deposits, cash, or in kind (in form of next season's inputs). These findings conform with those of Natraj *et al*. 2024 that blockchain enabled platforms increase profitability of smallholder farmers. Furthermore, with blockchain enabled value chain operations, barley farmers would be able to secure financial credit from other institutions and lenders for other consumption needs such as medical bills and school fees, with an assurance (both to the farmer and the lender) of timely payback upon delivery of barley output to Company B. This enabled adopting farmers to avoid distress sales of their barley which would attract lower prices and consequent lower gross margins (Georgen & Skoff, 2020).

The current findings enhance the understanding that blockchain technology improves the performance in terms of productivity and gross margin of smallholder farmers when incorporated in crop-value chains in rural communities. Overall, the present ESR results fit with the random utility theory that farmers are rational in decision making and that they choose to adopt a technology only if they derive maximum net benefit in terms of productivity and gross margin from their choice.

## 4.5 Blockchain technology implementation framework based on challenges and solutions

The aim of objective four was to identify and prioritize blockchain implementation challenges and their solutions in order to come up with an implementation framework based on Uganda's barley value chain context.

### 4.5.1 Challenges identified from the cross-sectional survey

As identified by the surveyed barley farmers, the challenges were diverse and complex, reflecting technical, farmer related, middlemen based, Company B related and then regulatory barriers. According to the survey results in Table 4.40, some of the most prominent challenges included middlemen’s fear of losing business (42.86%), which resonates with studies highlighting intermediaries' reluctance due to potential job displacement as blockchain could automate verification and transactions (Kshetri, 2018). Farmers also reported having no phones as a prominent barrier (22.45%), aligning with research that emphasizes digital access as a foundational requirement for adopting blockchain in rural settings (Kamilaris *et al*., 2019).

Other major challenges included a limited loyalty/trust from farmers towards Company (16.73%) and inadequate top management support (17.96%), which are consistent with findings that strong organizational commitment and clear communication are essential for successful technology integration (Treiblmaier, 2019). Furthermore, farmers identified inadequate government support (18.37%) and the absence of non-compliance handling rules (23.67%), which underscore the need for regulatory frameworks and strategic guidance to build trust in blockchain systems (Casino *et al*., 2019).

**Table 4.40:** Challenges facing blockchain technology implementation as identified by farmers

| Challenge | Share of farmers who said Yes to the given challenge (%) |
|---|---|
| Complexity | 1.22 |
| Incompatibility | 2.04 |
| High initial and implementation costs | 0.82 |
| Negative farmer attitude towards blockchain technology | 9.80 |
| No phone ownership | 22.45 |
| Limited funds from Company B | 6.94 |
| Limited blockchain knowledge of Company B staff | 15.10 |
| Limited blockchain knowledge from farmers | 9.80 |
| Limited loyalty/trust from farmers towards Company B | 16.73 |
| Inadequate top management support and commitment | 17.96 |
| Middlemen’s fear of losing business | 42.86 |
| Unclear implementation guidelines | 32.24 |
| Absence of rules for handling non-compliance | 23.67 |
| Inadequate government support | 18.37 |
| Other challenges | 18.78 |

### 4.5.2 Results of the implementation challenges as prioritized by analytic hierarchy process

The identified challenges from the survey together with the ones identified from literature review and stakeholder consultations were grouped in five categories and then prioritized to identify the most critical ones. The prioritization was achieved using analytic hierarchy process (AHP), a form of MCDMM. Prior to data collection, 5 challenge categories (criteria) and 14 sub -challenges (sub criteria) were considered following literature review and stakeholder consultations. During fieldwork, an additional sub criterion of limited trust/loyalty from farmers was suggested for inclusion in the pairwise matrices construction of the farmer-based challenge criterion, making a total of 15 sub-criteria.

The AHP results are presented in Tables 4.41 and 4.42. Following the recommendation from Rahman *et al*. (2019) and Sangka *et al*. (2019) that AHP techniques benefit from using fewer respondents for more accurate judgments, the analysis was conducted across four stakeholder groups. These groups comprised of two farmer groups (FG 1 and FG 2), three middlemen (MM 1, MM 2, and MM 3), three field staff officers from Company B (FS 1, FS 2, and FS 3), and two mid-level managers from Company B (MLM 1 and MLM 2). In total, 10 respondents were included in the analysis. The consistency ratios (CR) of the analysed stakeholder groups as well as for individuals were all below Saaty's acceptable recommendation of less or equal to 0.1 (i.e.CR=≤ 0.1) (Saaty, 1990), indicating that their responses were consistent.

**Table 4.41:** Priority weights of blockchain implementation challenges and sub-challenges, according to stakeholder analysis groups

| | Weights according to analysis groups | | | | | Weights according to analysis groups | | | |
|---|---|---|---|---|---|---|---|---|---|
| Criteria (Challenge category) | Farmer groups | Middlemen | Company B field staff | Company B mid-level managers | Sub-criteria (Sub-challenges) | Farmer groups | Middlemen | Company B field staff | Company B mid-level managers |
| CR Values | 0.062 | 0.024 | 0.029 | 0.029 | | | | | |
| BCT based challenge | $0.086^{e}$ | $0.083^{e}$ | $0.090^{e}$ | $0.094^{e}$ | CR Values | 0.046 | 0.026 | 0.005 | 0.046 |
| | | | | | Complexity | $0.049^{a}$ | $0.048^{a}$ | $0.018^{b}$ | $0.016^{c}$ |
| | | | | | Compatibility | $0.022^{b}$ | $0.022^{b}$ | $0.056^{a}$ | $0.030^{b}$ |
| | | | | | Initial cost | $0.014^{c}$ | $0.013^{c}$ | $0.016^{c}$ | $0.048^{a}$ |
| Farmer based challenge | $0.315^{a}$ | $0.278^{a}$ | $0.313^{a}$ | $0.221^{b}$ | CR Values | 0.066 | 0.022 | 0.029 | 0.024 |
| | | | | | Negative attitude | $0.061^{c}$ | $0.029^{d}$ | $0.035^{d}$ | $0.030^{d}$ |
| | | | | | No phone ownership | $0.033^{d}$ | $0.039^{c}$ | $0.051^{c}$ | $0.033^{c}$ |
| | | | | | Limited knowledge | $0.086^{b}$ | $0.068^{b}$ | $0.064^{b}$ | $0.092^{a}$ |
| | | | | | Limited trust/loyalty | $0.136^{a}$ | $0.142^{a}$ | $0.163^{a}$ | $0.065^{b}$ |
| Company B based challenge | $0.233^{c}$ | $0.254^{b}$ | $0.286^{b}$ | $0.369^{a}$ | CR Values | 0.023 | 0.016 | 0.026 | 0.023 |
| | | | | | Limited financial resources | $0.049^{b}$ | $0.031^{c}$ | $0.074^{b}$ | $0.100^{b}$ |
| | | | | | Inadequate top management support | $0.143^{a}$ | $0.168^{a}$ | $0.142^{a}$ | $0.208^{a}$ |
| | | | | | Staff limited knowledge | $0.041^{c}$ | $0.055^{b}$ | $0.070^{c}$ | $0.059^{c}$ |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Middlemen based | 0.250[b] | 0.226[c] | 0.135[d] | 0.150[d] | CR Values | 0.000 | 0.000 | 0.000 | 0.000 |
| | | | | | Fear of losing business | 0.167[a] | 0.104[b] | 0.108[a] | 0.121[a] |
| | | | | | No reward strategy from Company B | 0.083[b] | 0.122[a] | 0.027[b] | 0.029[b] |
| Regulatory based | 0.117[d] | 0.159[d] | 0.176[c] | 0.167[c] | CR values | 0.029 | 0.015 | 0.008 | 0.029 |
| | | | | | Unclear implementation guidelines | 0.053[a] | 0.039[c] | 0.023[c] | 0.043[b] |
| | | | | | Unclear rules for non-compliance | 0.045[b] | 0.074[a] | 0.126[a] | 0.087[a] |
| | | | | | Inadequate government support | 0.018[c] | 0.047[b] | 0.027[b] | 0.037[c] |

**Note:** Super scripts a, b, c, d, and e represent the order of importance/criticality of a challenge category/sub-challenge from most critical, a, critical to least critical, e.

**Results of stakeholder analysis group 1; Farmer groups:** The AHP results for the farmer groups showed that the most critical challenge category was farmer-based challenge, with a weight of 0.315. Within this category, the top priority sub-challenge was the lack of trust/ loyalty from farmers, weighted at 0.136. Limited trust issues arose when farmers who received inputs from Company B's stores through blockchain technology were unable to supply their barley to Company B, instead choosing to side-sell to middlemen. This behaviour was often driven by the need to address non-production expenses, such as school fees and medical bills, during the growing season. Under financial pressure, farmers were compelled to sell their produce to middlemen, who provided immediate cash, leaving the farmers unable to fulfil their contractual obligations with Company B, despite having received production resources through blockchain technology.

> Further, in the course of group discussion, FG 1 emphasized this concern by saying that "o*ur disloyalty to Company B is often inadvertent, as we find ourselves in circumstances beyond our control. For instance, we cannot let our children be sent home from school or allow our wives to die in childbirth just to uphold our blockchain contract with Company B. In these situations, the middlemen step in to bail us out".*

This study finding aligns with the findings of Tuyen *et al*. (2022) who identified lack of trust as the primary challenge in contract farming, with side selling being one of the main manifestations of this distrust. While Kabwe *et al*. (2018) found that farmers' lack of trust in Zimbabwe and Zambia's cotton supply chains stemmed from lack of pricing transparency, transparency was not the source of distrust among farmers in this study, as blockchain had addressed this issue.

The second most important challenge category was the Middlemen based challenge (weight =0.250) with fear of losing business (weight=0.167) as the priority sub-challenge. This implies that with the introduction of blockchain technology which was encouraging the direct transactions between the farmers and Company B, paused threat to the existence of middlemen in the barley value chain. Because blockchain technology integration ensures transparency, middlemen's control over information and pricing was potentially reduced. Eventually, the middlemen's fear to lose their trade, lured them into persuading farmers to sell their barley at various stages of growth, often convincing farmers to go along with these deals. This finding is consistent with those of Wang *et al*. (2019) and Yogarajan *et al*. (2023) who reported that blockchain technology disintermediates supply chains.

Furthermore, according to the farmer groups, Company B based challenge category (weight=0.233) was the third critical challenge, and in it, inadequate top management support (weight=0.143) was the top critical sub-challenge that required to be addressed first. The probable implication for this rating could be that farmers were aware of the role of Company B in the implementation process of blockchain. Also, the top-level managers' lack of dedication was evident in their reluctance to work toward ending the outsourcing of barley from neighbouring countries that competed with Ugandan barley. Consequently, farmers thought that senior management should be in charge of focusing efforts on controlling this vice, which was impeding the adoption of blockchain. In the course of group discussions, FG 2 participants in Bukwo district unanimously reported:

> *"Since we are close to the border, Kenyan barley consistently outcompetes ours. Kenya produces more barley than we do, and occasionally their barley is of higher quality, therefore Company B prefers their barley over ours. Other than waiting for the senior managers to intervene and halt this, there is nothing we can do about it.*

This finding is corroborated by Van Hoek's (2019) research, which found that senior managers' commitment and support are crucial for the effective integration of blockchain-based technologies in businesses.

From the perspective of farmer groups, the least critical challenge category was blockchain based challenges, which received a low weight of 0.086, with complexity being the primary sub-challenge, weighted at 0.049. The low weight assigned to blockchain based challenges suggests that farmers did not view these as significant compared to other challenge categories. However, it is important to note that farmers did perceive blockchain technology to be complex, ranking it as the top sub-challenge. Complexity, as defined by De Castro (2020), refers to the extent to which blockchain technology was thought to be challenging to use and comprehend. This perception of complexity is reasonable, given the low literacy rates prevalent among rural farmers, coupled with the novelty of blockchain. The farmers' rating of blockchain technology as complex may have stemmed from these factors. Clohessy and Acton (2019) support this finding, noting that perceived complexity of blockchain technology impedes its implementation in organizations. The farmer groups' opinions were always consistent with a few exceptions, for example, FG 1 ranked Company B based challenge as the second most important.

**Results of stakeholder analysis group 2; Middlemen:** Comparable to farmer groups' priority judgements of farmer-based challenge category (weight=0.315), the middlemen indicated that farmer-based challenge category (weight=0.278), was most critical. Within this category, both groups identified limited trust/loyalty from the farmers toward Company B as the key sub-challenge, with the middlemen rating it at 0.142 compared to the farmers' 0.136. The close alignment in these ratings by both farmer groups and middlemen, underscores the significance of farmer-based challenges, particularly the one of limited trust and loyalty, as crucial factors to be addressed for the successful implementation of blockchain technology. In one of the key informant interviews, middleman, MM 1 retorted:

> *"The farmers are patient until the end of the season to supply barley to Company B and get paid, yet they are faced with daily demands for cash. They often run to us for financial assistance in exchange for the growing barley".*

The purportedly impatience of the farmers, fostered by lack of liquidity may have pushed farmers to sell their produce to middlemen offering cash on hand, even if they had pre-existing blockchain contracts with Company B. Consequently, farmers were disloyal to Company B, which hampered blockchain technology implementation process. This finding is consistent with that of Ton *et al*. (2018), who highlighted that farmers often struggle with honouring contract arrangements, primarily due to the need for immediate cash to cover non-production expenses.

Unlike the farmers, all the middlemen identified Company B-based challenge as the second most important challenge category (weight=0.233), with inadequate top management support (weight=0.143) emerging as the top sub-challenge, aligning with the farmers' perspectives on this particular sub-challenge. As a major player in the barley value chain, serving as an input provider, farmer trainer, and buyer of barley output, Company B's influence in the introduction and widespread adoption of Blockchain Technology could not be underrated. The fact that middlemen and field staff (see analysis group 3) ranked Company B as the second most critical challenge, while mid-level managers regarded it as the top challenge (see analysis group 4), suggests that the blockchain technology implementation process might not have received adequate support, particularly from top-level managers.

Top-level managers, responsible for critical decisions around investments and resource allocation, may have shown caution regarding the potential benefits of blockchain technology due to its disruptive nature and high implementation costs. Consequently, they offered limited and calculated support for its adoption. This finding is consistent with other studies on technology adoption, which often highlight that insufficient support and commitment from top management impedes implementation efforts (Yadlapalli *et al*., 2022). Similar cynicism about the value and returns of new technologies has often been observed in other sectors, posing challenges in scaling innovations like blockchain technology (Lohmer *et al*., 2022).

The third most critical category according to the middlemen, was the middlemen-based challenge which was weighted at 0.226. Under the middlemen-based challenge category, absence of a rewarding strategy from Company B to the middlemen for barley delivered on behalf of the farmers (weight=122) was the priority sub-challenge. Due to poor road infrastructure and the long distances between farming households and Company B's buying centres, farmers often struggled to personally deliver their produce, even under blockchain contractual arrangements. As a result, middlemen took on the role of transporting and delivering the barley on behalf of the farmers. During this process, the farmers would receive notifications about the quantities delivered and the payments made to the middlemen. Payments were sometimes wired directly to the farmers' bank accounts or mobile phones.

Despite the middlemen's efforts, they often felt underappreciated or cheated, as they were not compensated by Company B for the time and energy spent transporting large volumes of barley on behalf of the farmers. Middleman, MM 3, had this to say in support of his rating of the absence of a rewarding strategy from Company B as top critical sub-challenge:

> *"We are just used as mere transporters; the farmers and the company benefit more than we do. The company does not take into account our effort, time, and the cost incurred to deliver the farmers' barley. I wish the company would do something about it"*

As a result of feeling undervalued, middlemen would often opt out of providing delivery services and instead register the barley under their own blockchain technology unique identifier codes rather than the farmers'. This allowed them to pay the farmers based on their bargaining power, often leading to the exploitation of farmers. These new insights into the intricate implementation process deepen the understanding of the ongoing challenges faced by rural small-scale crop value chains as they strive to adopt innovations like blockchain technology. Kaiser and Barstow (2022) support this finding by arguing that lack of reliable transportation infrastructure in rural farming communities reduces farmers' access to markets and inhibit their ability to adopt modern farming practices and innovative technologies, like blockchain technology.

The least important challenge according to all the middlemen was the Blockchain based challenge category (weight=0.083), and in it, complexity of blockchain (weight=0.048) was the critical sub-challenge, parallel to the farmer groups' judgement. Like the smallholder farmers, middlemen found the decentralized nature of blockchain overwhelming, as it required their records to be immutably stored on the blockchain technology system. The process was prolonged, involving numerous data entries, which proved to be particularly daunting for middlemen, who generally had limited familiarity with advanced technologies. Their usual role of simply buying and delivering goods was disrupted, adding complications to the integration of blockchain into the barley supply chain operations. Research by Mavilia and Pisani (2022), and Antonucci *et al*. (2019) also highlighted that blockchain complexity poses significant implementation challenges, especially in value chains involving smallholder farmers and intermediaries. The opinions of the middlemen were always consistent with slight disparities, for instance, MM 2 indicated middlemen-based challenges as top most challenge category.

**Stakeholder analysis group 3; Company B field staff:** All the Company B field staff, except FS 1, rated farmer -based challenges as more critical (weight=0.313) than Company B based challenge (weight=0.286), regulatory based challenges (weight=0.176) and middlemen-based challenge (weight=0.135) categories. In their opinions, the most critical sub-challenges under each challenge criteria, respectively, were: limited trust/loyalty (weight=0.163), inadequate top management support (weight=0.142), no rules for handling non-compliance (weight=0.126), and fear of losing business (weight=0.108). The rating of regulatory based challenge category as third most critical by Company B field staff, and mid-level managers (see analysis group 4), brings to light the rationale of policies and regulations in the implementation process of innovations like blockchain technology.

For an innovation to be successfully implemented, it has to be supported by well-defined policies and guidelines from all stakeholders and the government. The absence of clear rules for handling the non-complying farmers to the blockchain contractual arrangements between the farmers and Company B made it difficult for the latter to recover the funds provided to farmers as advance inputs for production. Without stringent regulations to prevent side-selling, business-oriented Company B faced potential losses, as farmers could sell their output to other buyers or middlemen.

**Table 4.42**: Detailed individual respondent weights of blockchain technology implementation challenges and sub-challenges

| | | Challenge and sub-challenge weights according to individual respondents' judgements | | | | | | | | | | Overall geomean weights |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Farmer Groups (FG) | | Middlemen (MM) | | | Company B Field Staff (FS) | | | Mid-Level Managers MLM) | | |
| | Challenge / Sub-challenge | FG 1 | FG 2 | MM 1 | MM 2 | MM 3 | FS 1 | FS 2 | FS 3 | MLM 1 | MLM 2 | |
| | CR Value | 0.091 | 0.079 | 0.093 | 0.067 | 0.036 | 0.050 | 0.070 | 0.084 | 0.061 | 0.031 | 0.016 |
| | BCT based challenge weight | $0.089^{e}$ | $0.080^{e}$ | $0.069^{e}$ | $0.076^{e}$ | $0.087^{e}$ | $0.093^{e}$ | $0.099^{e}$ | $0.069^{e}$ | $0.080^{e}$ | $0.109^{e}$ | $0.089^{e}$ |
| Sub-challenges | CR Values | 0.046 | 0.047 | 0.046 | 0.003 | 0.047 | 0.000 | 0.046 | 0.000 | 0.046 | 0.046 | 0.001 |
| | Complexity | $0.043^{a}$ | $0.053^{a}$ | $0.034^{a}$ | $0.049^{a}$ | $0.052^{a}$ | $0.009^{b}$ | $0.031^{b}$ | $0.017^{b}$ | $0.016^{c}$ | $0.015^{c}$ | $0.033^{b}$ |
| | Compatibility | $0.028^{b}$ | $0.017^{b}$ | $0.022^{b}$ | $0.016^{b}$ | $0.022^{b}$ | $0.076^{a}$ | $0.049^{a}$ | $0.035^{a}$ | $0.025^{b}$ | $0.036^{b}$ | $0.035^{a}$ |
| | Initial cost | $0.018^{c}$ | $0.011^{c}$ | $0.014^{c}$ | $0.009^{c}$ | $0.014^{c}$ | $0.009^{b}$ | $0.019^{c}$ | $0.017^{b}$ | $0.039^{a}$ | $0.057^{a}$ | $0.021^{c}$ |
| | Farmer Based challenge weight | $0.305^{a}$ | $0.309^{a}$ | $0.385^{a}$ | $0.122^{d}$ | $0.358^{a}$ | $0.221^{b}$ | $0.363^{a}$ | $0.362^{a}$ | $0.221^{b}$ | $0.211^{b}$ | $0.285^{a}$ |
| Sub -challenges | CR values | 0.053 | 0.083 | 0.091 | 0.072 | 0.081 | 0.079 | 0.053 | 0.079 | 0.081 | 0.045 | 0.015 |
| | Negative attitude | $0.067^{c}$ | $0.053^{c}$ | $0.033^{d}$ | $0.017^{c}$ | $0.032^{d}$ | $0.027^{c}$ | $0.043^{d}$ | $0.034^{d}$ | $0.028^{d}$ | $0.032^{c}$ | $0.037^{d}$ |
| | No phone ownership | $0.034^{d}$ | $0.031^{d}$ | $0.099^{b}$ | $0.010^{d}$ | $0.046^{c}$ | $0.019^{d}$ | $0.088^{b}$ | $0.074^{b}$ | $0.049^{c}$ | $0.022^{d}$ | $0.041^{c}$ |
| | Limited knowledge | $0.081^{b}$ | $0.086^{b}$ | $0.058^{c}$ | $0.044^{b}$ | $0.087^{b}$ | $0.052^{b}$ | $0.069^{c}$ | $0.066^{c}$ | $0.084^{a}$ | $0.092^{a}$ | $0.077^{b}$ |
| | Limited trust/loyalty | $0.125^{a}$ | $0.14^{a}$ | $0.196^{a}$ | $0.049^{a}$ | $0.192^{a}$ | $0.123^{a}$ | $0.164^{a}$ | $0.189^{a}$ | $0.056^{b}$ | $0.065^{b}$ | $0.131^{a}$ |
| | Company B based challenge weight | $0.198^{c}$ | $0.279^{b}$ | $0.269^{b}$ | $0.195^{b}$ | $0.234^{b}$ | $0.364^{a}$ | $0.217^{b}$ | $0.289^{b}$ | $0.406^{a}$ | $0.324^{a}$ | $0.283^{b}$ |
| | CR Values | 0.047 | 0.008 | 0.011 | 0.075 | 0.047 | 0.075 | 0.000 | 0.047 | 0.047 | 0.008 | 0.0051 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sub -challenges | Limited financial resources | 0.049[b] | 0.049[c] | 0.032[c] | 0.019[c] | 0.037[c] | 0.084[b] | 0.043[b] | 0.073[b] | 0.102[b] | 0.094[b] | 0.058[b] |
| | Inadequate top management support | 0.116[a] | 0.176[a] | 0.201[a] | 0.121[a] | 0.138[a] | 0.242[a] | 0.043[b] | 0.170[a] | 0.239[a] | 0.175[a] | 0.167[a] |
| | Limited knowledge of some staff | 0.031[c] | 0.054[b] | 0.036[b] | 0.055[b] | 0.059[b] | 0.038[c] | 0.130[a] | 0.046[c] | 0.065[c] | 0.053[c] | 0.058[b] |
| Middlemen based challenge weight | | 0.291[b] | 0.218[c] | 0.115[d] | 0.434[a] | 0.196[c] | 0.139[d] | 0.124[d] | 0.134[d] | 0.157[c] | 0.144[d] | 0.185[c] |
| Sub -challenges | CR Values | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | Fear of losing business | 0.194[a] | 0.146[a] | 0.013[b] | 0.362[a] | 0.098[a] | 0.104[a] | 0.108[a] | 0.100[a] | 0.118[a] | 0.124[a] | 0.128[a] |
| | No reward strategy from Company B | 0.097[b] | 0.073[b] | 0.103[a] | 0.072[b] | 0.098[a] | 0.035[b] | 0.016[b] | 0.033[b] | 0.039[b] | 0.021[b] | 0.057[b] |
| Regulatory based challenge weight | | 0.117[d] | 0.113[d] | 0.161[c] | 0.174[c] | 0.124[d] | 0.182[c] | 0.197[c] | 0.146[c] | 0.136[d] | 0.211[b] | 0.158[d] |
| Sub -challenges | CR Values | 0.016 | 0.046 | 0.064 | 0.046 | 0.011 | 0.047 | 0.075 | 0.047 | 0.016 | 0.046 | 0.004 |
| | Unclear implementation guidelines | 0.046[b] | 0.059[a] | 0.098[a] | 0.034[c] | 0.008[c] | 0.030[b] | 0.021[c] | 0.019[c] | 0.029[c] | 0.066[c] | 0.039[b] |
| | Unclear rules for non-compliance | 0.052[a] | 0.038[a] | 0.044[b] | 0.085[a] | 0.061[a] | 0.139[a] | 0.131[a] | 0.096[a] | 0.074[a] | 0.104[a] | 0.087[a] |
| | Inadequate government support | 0.019[c] | 0.016[c] | 0.019[c] | 0.054[b] | 0.054[b] | 0.013[c] | 0.046[b] | 0.031[b] | 0.033[b] | 0.042[c] | 0.033[c] |

**Note:** Super scripts a, b, c, d, and e represent the order of importance/criticality of a challenge category/sub-challenge from most critical, a, to least critical, e.

During the interviews, one of the key informants, FS 3, who rated absence of rules for non-compliance as the most critical sub-challenge said that:

> "*There is no mechanism to compel farmers to fulfil their agreements. We cannot pressure farmers to supply barley to us, as maintaining positive relationships with them is essential for continued production. The absence of binding clauses in the blockchain implementation process leaves the company powerless to prevent side-selling, leading to financial losses".*

This finding concurs with that of Akella *et al.* (2023), who noted that the lack of best practices and guidelines is a significant obstacle to blockchain implementation in the agrifood sector. Malik *et al*. (2021) also found that unclear standards and policies deter organizations from adopting blockchain at scale, reinforcing the critical role of regulatory clarity for the success of blockchain solutions in business environments.

Again, all Company B field staff unanimously rated blockchain based challenges as the least critical challenge category (weight=0.090). In contrast to the previous groups (farmers and middlemen), who prioritized complexity as the most important sub-challenge within the blockchain based challenge category, the field staff of Company B considered compatibility to be more critical (weight=0.057), with complexity ranked second (weight=0.018). Blockchain compatibility was assessed by how well it fit with the existing values, experiences, and needs of farmers, middlemen, and Company B, as well as how easily it integrated with Company B's current systems and processes. This approach aligns with Roger's (2003) definition of compatibility, which emphasizes the importance of a technology's fit with the users' existing systems and practices.

The field staff reported that blockchain technology was somehow incompatible with the existing farmer records keeping and payment systems at the buying centres. During key informant interviews, field staff, FS 1, expressed frustration, stating that:

> *"Sometimes, the blockchain system prevents us from paying farmers and middlemen, even when they have travelled long distances to deliver barley to the buying centres. The system is highly dependent on network availability and becomes unreliable if the network is unstable.".*

The frustration of FS 1 suggests that the incompatibility issue was exacerbated by unstable network connectivity in areas with limited mobile telecommunication boosters. As a result, there were frequent failed attempts to enrol farmers on the blockchain app and difficulties in processing payments for both farmers and middlemen upon barley delivery.

Moreover, network instability could completely halt operations at Company B's buying centres when the blockchain system was offline. The complete reliance on and frequent failure of the blockchain system network for most operations at the buying centre highlighted its incompatibility with previously used systems that could still process transactions on low-bandwidth networks. This finding aligns with the observations of De Castro *et al*. (2020), which indicated that firms may be reluctant to integrate blockchain if they perceive it as incompatible with their existing systems and infrastructure.

**Stakeholder analysis group 4: Company B mid-level managers:** Meanwhile, all the mid-level managers indicated that Company B based challenge category (weight=0.369) was the top critical challenge that required addressing for successful blockchain technology implementation. This ranking differs from that of the previous three groups (farmers, middlemen, and field staff) who regarded farmer-based challenge category as the most critical of all. The farmer groups had rated Company B based challenge category as third critical challenge (weight=0.233), while middlemen and field staff had prioritized it as second critical with weights of 0.254 and 0.286 respectively. Within the Company B based challenge category, the mid-level managers identified inadequate top management support as most critical sub-challenge (weight=0.208), consistent with the perceptions of other groups. The second most important sub-challenge was limited financial resources (weight=0.100).

This ranking of Company B based challenge category as most critical by mid-level management buttresses the importance of organizational factors such as top management commitment, and financial resources, in the implementation process of innovations like blockchain technology. Top management plays a key role in coordinating resources, providing direction, and ensuring alignment across departments to meet company objectives related to blockchain integration. According to the mid-level managers' analysis, however, these managerial responsibilities were not adequately fulfilled by senior leadership, which compromised the entire blockchain technology implementation process. Insofar as the challenge of inadequate top management support was concerned, the mid-level manager, MLM 1, narrated during the interview:

*"We usually follow order from above while carrying out our duties. For instance, we did not receive any directives on how to address the overarching issue of barley importation from Kenya which would be disguised as Ugandan. This undermined the competitiveness of our farmers' produce, even though blockchain technology was introduced to tackle such challenges".*

The narration of MLM 1 suggests a top-down decision-making culture within Company B, where employees primarily act based on directives from higher management. In this case, the lack of guidance regarding the issue of barley importation disguised as Ugandan, despite the introduction of blockchain technology to address such challenges, indicates a gap in leadership. This lack of clear direction may have undermined the potential effectiveness of blockchain technology in safeguarding local farmers' competitiveness. It also highlights a possible disconnect between technology implementation and strategic management, where the necessary steps to tackle critical issues are not being communicated or enforced from the top. The same finding was outlined by Sendros *et al*. (2022) that leadership and organizational support are key to implementing and realizing blockchain's potential benefits, such as traceability and supply chain transparency in agriculture.

According to the mid-level managers, farmer-based challenge category followed as second in priority (weight=0.221), with limited blockchain knowledge among the farmers as the top sub-challenge (weight=0.092). Company B's mid-level managers uniquely prioritized limited blockchain knowledge among farmers as top critical sub-challenge in the farmer-based challenge category, unlike all other groups where it was consistently rated as the second most critical, after limited trust/loyalty. Explicitly, the weights assigned to limited knowledge sub-challenge were 0.086 by farmers, 0.068 by middlemen, and 0.064 by the field staff.

Mid-level managers, drawing on their managerial and supervisory experience, may have noticed during the implementation process that smallholder barley farmers lacked sufficient knowledge and understanding of blockchain, impeding its effective implementation. This emphasizes the need for continuous provision of blockchain-tailored trainings to farmers, not only at the initial enrolment stage but also throughout the usage period. This finding aligns with research by Gumbi *et al*. (2023), who noted that nascent digital innovations, such as blockchain, require users to possess rich knowledge and technical skills for successful adoption. Without these, the implementation of blockchain in agriculture could face significant challenges.

Additionally, regulatory based challenges were third in importance (weight=0.167) with absence of rules for handling non-compliance (weight=0.087) as top critical sub-challenge. Furthermore, all the mid-level managers indicated blockchain-based challenges (weight=0.029) as the least critical category. In this category, initial cost strikingly emerged as the most critical sub-challenge (weight=0.048), in contrast to all previous groups where it consistently ranked as the least critical. Specifically, farmers assigned it a weight of 0.014, middlemen gave it a weight of 0.013, and the field staff assigned it a weight of 0.016.

The prioritizing of initial cost of blockchain as top sub-challenge by mid-level managers could be comprehensible given their close administration ties with top-level managers who are involved in making key decisions including financial related ones. This indicates that technologies like blockchain technology often require substantial upfront investment and implementation costs, which can be burdensome to companies in the developing countries like Uganda. Similarly, Al Amin *et al*. (2023) highlighted that high costs are a significant barrier to blockchain adoption in supply chain firms, reinforcing the financial challenges associated with implementing such innovations.

The views of the mid-level managers were largely consistent, with only a few variances. For example, MLM 1 ranked the middlemen-based category as the third most critical (weight=0.157), while MLM 2 rated the regulatory-based category as the second most important (weight=0.211).

Overall, geometric means were calculated for the weights across all respondents. The results revealed that the top three priority challenge categories for blockchain implementation in the barley value chain were the farmer-based challenge category (weight=0.285), closely followed by the Company B-based challenge category (weight=0.283), and the middlemen-based challenge category (weight=0.185). Although the regulatory-based challenge category ranked fourth, it still carried a significant weight of 0.158 close to the weight of middlemen-based challenge category. The least critical challenge category was the blockchain-based challenge (weight=0.089).

The rating of blockchain-based challenge category as the least critical by all analysis groups, supported by the overall geometric mean calculations, reinforces the initial assumption that BanQu blockchain software was well-suited for integration into Uganda’s barley value chain. In addition, it indicates that the technology was appropriate for addressing the core challenges within the value chain, provided it was implemented correctly. This finding aligns with Kshetri's

(2021) research, which showed that BanQu blockchain successfully addressed cassava value chain challenges in Zambia. Overall, the opinions of individual respondents and analysis groups were largely consistent with the overall judgment from the analysis. The graphical representation of the overall judgement of respondents is presented in Figure 4.5.

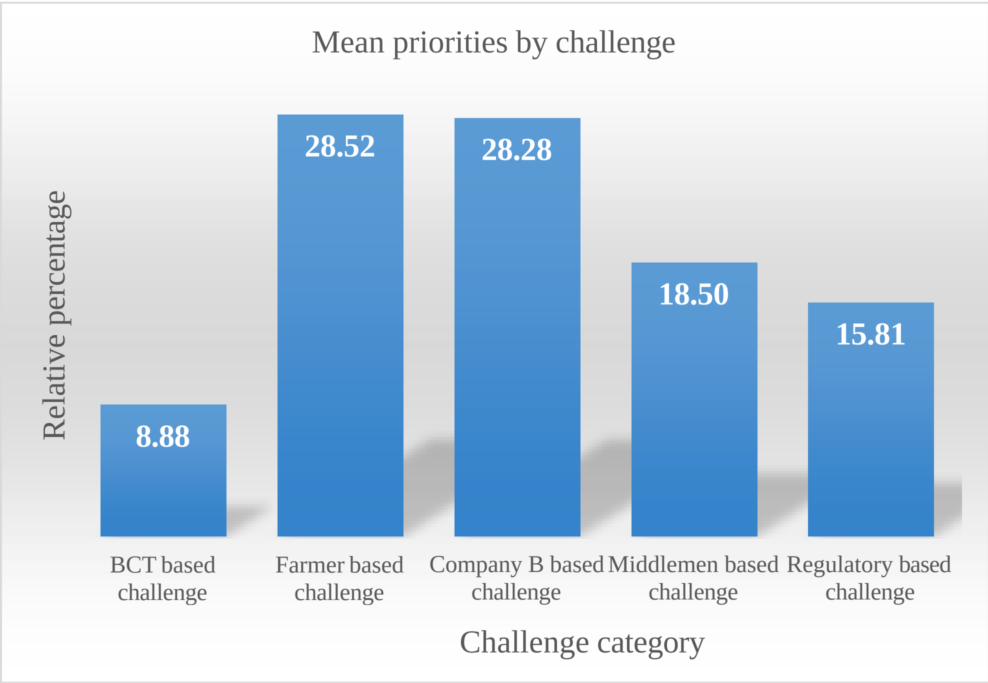


**Figure 4.5:** Overall mean priorities by challenge categories

The top priority sub-challenges identified in their hierarchy of importance were as follows: For farmer-based challenges, limited trust/loyalty from farmers ranked highest (0.131), followed by limited knowledge of blockchain (0.077), lack of phone ownership (0.041), and negative attitudes toward blockchain (0.037). In Company B-related challenges, inadequate top management support was most critical (0.167), while limited blockchain knowledge among staff and financial constraints each had a weight of 0.058. Among middlemen-related challenges, fear of losing business was the primary sub-challenge (0.128), while absence of a reward strategy from Company B followed with a weight of 0.057. For regulatory challenges, the absence of rules for non-compliance (0.087) was top prioritized, with unclear implementation guidelines (0.039) and insufficient government support (0.033) ranked second and third. Finally, within blockchain-related challenges, compatibility (0.035) was the leading sub-challenge, followed by complexity (0.033) and high initial costs (0.021). These challenges and their sub-challenges, in their hierarchy, form the basis for the proposed solutions below.

### 4.5.3 Suggested solutions for addressing blockchain implementation in the barley value chain

Based on insights gathered from key informant interviews and group discussions, solutions were proposed that directly addressed the prioritized challenges and their sub-challenges. These solutions are presented in alignment with the specific sub-challenges identified under each challenge category, as detailed below.

**Suggested solutions to address farmer-based challenges:** Stakeholders suggested a legally binding blockchain-enabled contract between farmers and Company B to curb side-selling and improve loyalty. They emphasized that the contract should be clearly explained to farmers before signing. This suggested strategy reflects a focus on securing loyalty and adherence to agreed terms, potentially leveraging blockchain's features of transparency and immutability. This was also noted by Lee *et al*. (2022) that blockchain enabled contracts can potentially substitute trust issues among stakeholders in supply chains if they are well executed. To address farmers' limited knowledge of blockchain, stakeholders proposed intensive training and sensitization programs before and during blockchain technology implementation. This reflects a proactive approach to overcoming this challenge, which is essential for boosting farmers' understanding and confidence in blockchain technology. Farmers' increased knowledge of blockchain could lead to higher adoption rates and continuous engagement with the technology, as noted by Chen and Shang (2022).

To tackle low mobile phone ownership, stakeholders suggested Company B to partner with telecom companies to provide affordable phones, funded by withholding an agreed upon portion of farmers' earnings upon barley supply. Additionally, Company B's field staff should conduct financial literacy sessions to help farmers save and purchase of mobile phones by the season's end. The savings tailored programmes are believed to enable farmers prioritize their needs and make informed decisions about investing in acquiring resources that facilitate their barley value chain processes such as mobile phones. This proposition by stakeholders is supported by the findings of Ntakyo *et al*. (2021), who noted that expanding financial education programs could equip communities with the knowledge needed for sound financial decisions.

**Suggested solutions to address Company B-based challenges:** Based on the group discussions and the interviews, the stakeholders suggested that there should be close and strengthened collaboration between the top-level managers and the lower-level team so that the blockchain implementation process is fully supported top-down. Specifically, efforts and commitment should be directed towards addressing the gaps in barley outsourcing so as to protect the local farmers. Stakeholders also highlighted the importance of allocating more funds to innovative technologies like blockchain, with particular emphasis on supporting farmer training programs and building skills of the company's technical team to ensure smooth implementation of the technology.

The stakeholder suggestions imply that commitment and engagement of senior management are crucial for resource allocation, strategic alignment, and motivating lower-level teams to adopt new technologies effectively. Also, enhanced collaboration fosters open communication, ensuring that all team members are aligned with the goals and processes associated with blockchain technology implementation. This finding is consistent with Reyes *et al*. (2016) and Koster and Borgman (2020) who emphasized the role of top management support in the implementation of most novel technologies including blockchain.

**Suggested solutions to address middlemen-based challenges:** To alleviate the concerns of middlemen about losing business, stakeholders recommended that Company B provide cash advances to farmers throughout the production cycle. This approach would enhance farmers' liquidity, reducing their dependence on middlemen to cover non-production expenses. By ensuring that farmers have sufficient cash flow during the barley growing season, their vulnerability to persuasive cash advances and bailouts from middlemen is diminished. A study by Albuquerque *et al*. (2024) supports this recommendation, indicating that liquidity-constrained farmers tend to sell more than 50% of their harvest more quickly and at lower prices compared to those who are not constrained.

Additionally, middlemen should be educated to stop bad practices, such as purchasing immature barley or importing it, as these practices contradict local sourcing guidelines. To incentivize better behaviour among the middlemen, stakeholders suggested that Company B introduces a commission system for middlemen based on the quantity of barley delivered to buying centres. This would discourage middlemen from registering farmers' barley under their own blockchain codes and underpaying them. An alternative solution proposed was for Company B to contract middlemen directly, similar to the way they contract farmers, ensuring business continuity and fostering a fair, win-win relationship between farmers, middlemen, and the company.

**Suggested solutions to address regulatory-based challenges:** To address regulatory challenges, stakeholders suggested strict measures such as penalizing farmers who fail to comply with blockchain contractual arrangements. Penalties could include withdrawal of the technology or withholding inputs for future seasons until outstanding supplies are fulfilled. Legal action could also be taken, with non-compliant farmers being held accountable in local council courts to minimize company losses. Once more, parish coordinators and farmer groups should also be empowered to monitor production and ensure supplies are delivered to Company B, reducing side-selling through community oversight, similar to rural table banking systems. The premise here is that local, community-based oversight fosters accountability within farmer groups, enhancing coordination and collective commitment. This approach ensures a reliable barley supply chain by discouraging side-selling. Kilelu *et al*. (2017) found similar results with dairy hubs in Kenya, where collective oversight by farmer groups minimized unscrupulous behaviours, such as side-selling, among members.

Furthermore, stakeholders also suggested that Company B collaborate with the government to draft clear guidelines/policies, roles, and responsibilities for blockchain implementation, ensuring accountability for all parties. For instance, the existing Memorandum of Understanding (MoU) between Company B and the government requires Company B to enforce local material sourcing and the government to reduce excise duties in return. Both parties should be held accountable for meeting their commitments. Well-defined guidelines provide a roadmap for all stakeholders involved in the implementation process. This clarity helps prevent misunderstandings and miscommunication, enabling smoother transitions. Jellason *et al*. (2024) expressed similar views, highlighting the necessity for effective governance and regulatory frameworks to facilitate the seamless implementation of blockchain in agrifood value chains.

Beyond just signing the MoU with Company B, the government should actively participate in the blockchain implementation process. Government representatives, from local council ones to district levels, along with mainstream agricultural extension officers, should collaborate with Company B's staff to raise awareness and train farmers on the benefits of blockchain, as this is essential for promoting community development. Additionally, the government should commit to improving rural road infrastructure to make them all-weather accessible, ensuring farmers could easily access Company B's buying centres for input collection and product delivery. A study by Song *et al*. (2022) offers empirical illustration of such a collaboration between the government, telecom companies (as BCT developers) and agricultural firms in the implementation of blockchain in China's agricultural supply chains, with each party's roles clearly defined.

**Suggested solutions to address blockchain technology-based challenges:** To address the blockchain technological challenges, stakeholders recommended that blockchain developers focus on simplifying the user experience. For instance, reducing the number of data entries required during enrolment would make the system less complex. Stakeholders also proposed a bottom-up approach in developing such technologies, ensuring consultations with end users to avoid incompatibilities between new and existing systems. A key suggestion was that the blockchain system should allow for data spooling from previously used systems to streamline the registration process. The stakeholders' suggestions imply that blockchain technologies should be designed with user needs and capacities in mind; otherwise, design limitations may obstruct their successful implementation and reduce potential advantages (Behnke & Janssen, 2020; Kamilaris *et al*., 2019). Additionally, continuous training tailored to both farmers and middlemen could enhance their understanding of blockchain, mitigating user difficulties.

Moreover, stakeholders proposed that Company B collaborate with telecommunication providers like MTN and Airtel to install more network boosters in the remote, hilly barley-producing areas. This would improve connectivity and ensure stable internet access at buying centres, leading to a more reliable blockchain system. To address the high initial costs of implementing technologies like blockchain, they also advised the government to adopt a cost-sharing approach with Company B, extending these innovations to smallholder farmers through public-private partnership (PPP) models. The plausible implication here is that with the shared objective of improving the performance of barley farmers in the study area by the government and the company, the PPP model would alleviate the challenge of initial costs of beneficial technologies like blockchain. This finding is supported by the findings of Moreddu (2016), who reported that PPP are accelerators of broader adoption of innovations in agriculture.

### 4.5.4 Proposed framework for successful blockchain technology implementation based on Uganda's context

Based on the identified and prioritized challenges and suggested solutions by the stakeholders in the barley value chain, the following fishbone like framework was proposed for successful blockchain technology implementation (Figure 4.6). This framework was based on eastern Uganda's barley value chain context, though it could be used to draw inferences in other countries. The direction and position of the arrows along the middle axis signify the criticality of a given challenge towards the overall goal of successful implementation of blockchain in Uganda.

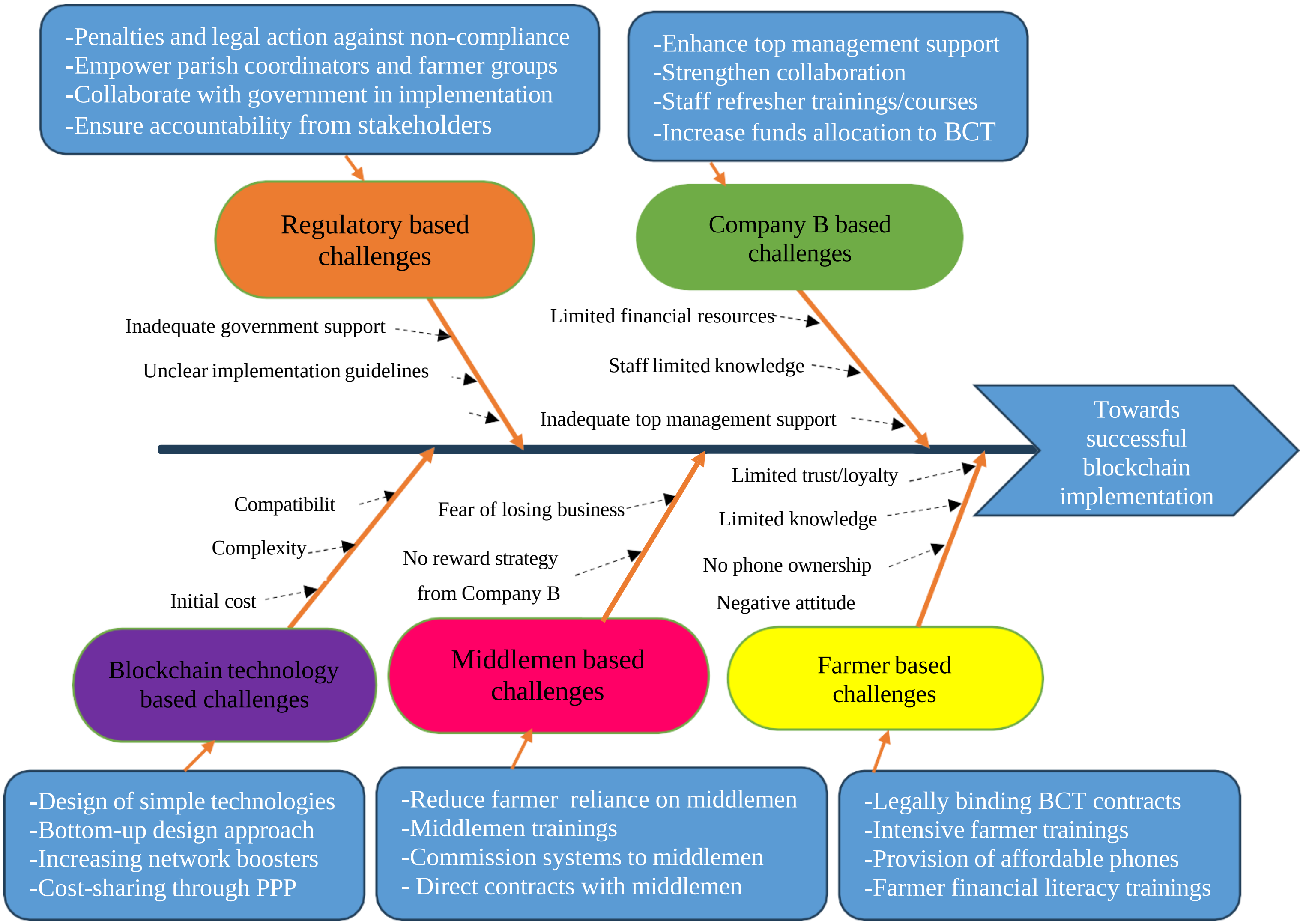


**Figure 4.6:** Framework for successful implementation of blockchain in the barley value chain

# CHAPTER FIVE

# CONCLUSIONS AND RECOMMENDATIONS

## 5.1 Conclusions

The following conclusions stem from the study objectives.

i. From the first objective, the study concluded that while subjective norms influenced perceived usefulness, farmer attitudes, image, and result demonstrability were stronger predictors of blockchain acceptance. Blockchain's relevance in the barley value chain further strengthened farmers' intention to adopt the technology. Farmers' perceived control significantly predicted perceived ease of use; however, ease of use did not have a notable effect on adoption intentions, suggesting that farmers prioritized usefulness, possibly due to the tailored training and support provided. Voluntariness enhanced perceived usefulness, underscoring the role of intrinsic motivation in technology acceptance, though it did not moderate the effect of subjective norms on behavioural intention. Social norms emerged as a key determinant of blockchain acceptance, with subjective norms, injunctive norms, normative reference groups, and behavioural sanctions shaping farmers' attitudes, which in turn positively influenced their adoption intentions. Overall, the findings reaffirm that farmers' attitudes are strong predictors of behavioural intention, consistent with the Theory of Planned Behaviour, and emphasize the importance of cultivating positive attitudes to enhance blockchain adoption in agricultural value chains.

ii. From the second objective, the study concluded that blockchain adoption and usage among smallholder barley farmers in eastern Uganda were shaped by a combination of socioeconomic, institutional, and infrastructural factors. Adoption was positively influenced by the frequency of blockchain-tailored training, network stability, production costs, land size, system compatibility, and phone ownership, but negatively affected by marital status, extension frequency, training cost, land tenure, distance to buying centres, and initial and marketing costs. Similarly, the extent of blockchain usage increased with farmers' sex, age, education level, training frequency, affordability of training, and group membership, but declined with larger land size, greater distance to buying centres, and higher initial costs, highlighting the significant influence of these contextual factors on technology adoption in smallholder farming systems across Sub-Saharan Africa.

iii. The results from the third objective showed that blockchain adopters achieved higher barley productivity and gross margins per acre than non-adopters, which would not have been the case had they not adopted. The adopting farmers consistently obtained higher gross margin across all scenarios studied. While non-adopting farmers had lower productivity and gross margin than adopting farmers, they would have achieved higher productivity than adopters if they had adopted. Additionally, if non-adopting farmers had adopted, their gross margin would have increased, though still remaining lower than that of the adopting farmers. If neither group had adopted blockchain technology, the non-adopting farmers would have achieved higher productivity than the adopting farmers. This suggests the presence of unobserved factors that contributed to differences between the two groups and justifies the use of the endogenous switching regression model to account for endogeneity. Overall, these findings indicate that blockchain adoption increased barley productivity and gross margins for barley farmers.

iv. From the fourth objective, farmer-based challenges ranked highest, with limited trust or loyalty as the top sub-challenge, followed by limited blockchain knowledge, lack of phone ownership, and negative attitudes. Company B-based challenges came next, led by inadequate top management support, followed by limited staff knowledge and financial constraints. Middlemen-based challenges ranked third, driven by fears of losing business and the absence of a reward strategy. Regulatory challenges followed, with the lack of rules for non-complying farmers as the top issue, alongside unclear guidelines and limited government support. Blockchain technology-related challenges ranked lowest, with compatibility, complexity, and high initial costs as key concerns.

    From the stakeholder consultations, solutions aligned with the prioritized challenge categories were proposed, including implementing legally binding blockchain-enabled contracts and intensive farmer training to curb side-selling and enhance knowledge; fostering top management collaboration, increased financing, and refresher training within Company B; offering farmers cash advances, educating middlemen on ethical practices, and introducing commission-based incentives; enforcing strict regulatory measures with community oversight and government collaboration to improve infrastructure and accountability; simplifying blockchain interfaces through a participatory, bottom-up design; expanding network coverage via telecom partnerships; and sharing implementation costs through public–private partnerships, all integrated within a proposed Fishbone framework to guide future blockchain adoption in Uganda's barley value chain and other agricultural systems.

## 5.2 Recommendations

i. From the first objective, the study recommended that to improve farmers' perceptions of blockchain's usefulness and ease of use, stakeholders should organize demonstrations and share success stories that highlight tangible benefits. Maintaining a voluntary approach to adoption will help foster positive attitudes. Stakeholders should also conduct targeted training sessions that focus on boosting farmers' image and confidence in using blockchain technology. Leveraging social norms by engaging influential figures in the farming community, like local leaders and successful adopters, to promote blockchain benefits. Emphasizing social norms could positively shape farmers' attitudes and intentions toward blockchain adoption.

ii. From the second objective, the study recommended that in order to enhance blockchain adoption, Company B should target younger and more educated farmers with tailored training, promote group learning for peer support, subsidize initial and training costs through broad public–private partnerships involving government, financial institutions, and development agencies, strengthen extension interactions through decentralized support hubs, and implement financial literacy programs to improve affordability and resource access.

iii. Based on objective three, the study recommends that to maximize productivity benefits, stakeholders and researchers should collaborate to organize information dissemination workshops showcasing the productivity and income differences between blockchain adopters and non-adopters. These workshops should emphasize the tangible benefits of blockchain, such as increased yields and higher gross margins, to encourage wider adoption. To address variations in farmers' unobservable traits, including risk tolerance, adaptability, and resource access, stakeholders should implement targeted support mechanisms. Providing entrepreneurial training tailored to these differences will help farmers adapt more effectively, facilitating smoother adoption and implementation of blockchain technologies.

iv. Based on objective four, several recommendations were made to strengthen blockchain implementation in the Ugandan barley value chain. To enforce agreements and minimize side-selling, stakeholders should introduce legally binding blockchain-enabled contracts that foster loyalty between farmers and Company B. These contracts must be simple, clear, and enforceable, accompanied by farmer education to build trust and ensure compliance. To strengthen Company B's internal capacity, top management should actively support blockchain initiatives, reduce outsourcing, and provide regular refresher training for technical teams to enhance their understanding and improve support for farmers during implementation. Additionally, to address challenges posed by middlemen, Company B should offer cash advances to reduce farmers' dependency on middlemen loans, educate intermediaries on ethical practices such as avoiding early crop purchases, and establish a commission system linked to supply volumes to encourage fair operations.

To address regulatory and technological challenges, stakeholders should implement strong enforcement measures, including penalties to ensure compliance with blockchain contracts and safeguard Company B's financial interests. Community oversight mechanisms should be enhanced by empowering local coordinators and farmer groups to monitor production and supply, while government investment in rural infrastructure should improve access to buying centres and reduce reliance on middlemen. Developers should simplify blockchain interfaces to accommodate varying levels of digital literacy and adopt a participatory, bottom-up approach involving farmers, middlemen, and Company B representatives in the design phase to ensure the technology meets user needs. Furthermore, improving network infrastructure through partnerships with telecom companies to install boosters in poorly connected areas and providing affordable blockchain-compatible devices will enhance functionality and accessibility. Finally, stakeholders should adopt the study's proposed Fishbone diagram as a practical framework to identify priority areas and guide focused interventions for blockchain implementation, with potential adaptation across other agricultural value chains in Uganda and beyond.

## 5.3 Areas for future research

Future research could track the long-term effects of blockchain adoption on farmers' productivity, income stability, and socio-economic status to understand its sustained impact over a longer time. Comparative studies across regions and crops would clarify if findings hold in diverse contexts, particularly for crops with unique value chains or market structures. Additional exploration of behavioural factors, such as trust, risk tolerance, and resistance to change, could offer insights into the nuances of technology adoption among farmers hesitant to adopt digital tools.

Also, examining the role of external support, including telecom companies, government subsidies, and farmer cooperatives, would highlight how partnerships help reduce adoption barriers sustainably. Targeted research on demographic factors, like gender and age, may reveal unique challenges and motivations, enabling more tailored training and support. Further studies could also explore blockchain's impact on broader social and environmental outcomes, such as community cohesion, conservation, and local employment, to offer a holistic view of its role in rural development. Finally, comparative research on blockchain technology and other digital technologies (like., AI or IoT solutions) would help policymakers and stakeholders identify the best-suited technologies for specific agricultural objectives.

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**APPENDICES**

**Appendix A: Survey questionnaire**

**EGERTON UNIVERSITY**

**BLOCKCHAIN TECHNOLOGY ACCEPTANCE, ADOPTION AND ITS EFFECT ON PRODUCTIVITY AND GROSS MARGIN QUESTIONNAIRE**

*(This information is strictly confidential and is to be used for statistical and academic purposes only.)*

## SECTION A: HOUSEHOLD IDENTIFICATION

| | CODE NAME |
|---|---|
| 1. QUESTIONNAIRE NUMBER | ……………………………………………………………. |
| 2. DISTRICT | ……………………………………………………………. |
| 3. SUB-COUNTY | ……………………………………………………………. |
| 4. PARISH | …………………………………………………………… |
| 5. VILLAGE | ……………………………………………………………. |
| 6. NAME OF INTERVIEWER | ……………………………………………………………. |
| 7. INTERVIEWER ID | …………………………………………………………… |
| 8. DATE | ……………………………………………………………. |
| 9. STARTING TIME | ……………………………………………………………. |
| 10. FINISHING TIME | …………………………………………………………… |

**TABLE OF CONTENTS**



**Introduction**

My name is Racheal Ninsiima, a PhD student of Agribusiness Management at Egerton University, Kenya. This survey is aimed at determining the acceptance, adoption and effect of blockchain technology on performance of barley farms in eastern Uganda. You have been selected because of your knowledge on barley farming and blockchain technology, however, your participation is voluntary. The information you provide will be for academic purposes only and will be treated with utmost confidentiality.

**SECTION A: HOUSEHOLD CHARACTERISTICS**

A1: **Provide the following details about the household head**

| Sex: 1 = Male , 0 = Female | Age (years) must be >18 | Marital status (CODE A) | Education level (years in school) | Main Occupation (CODE B) ..Must pick one | Other occupation (CODE B)…can pick more than one |
|---|---|---|---|---|---|
| | | | | | |

**CODE A: Marital Status:** 1=Married 2=Single/Divorced/Widowed

**CODE B: Occupation:** 1=Barley farming, 2=other crop farming, 3= Livestock farming, 4= Agricultural produce trader (other than barley, and not own produce), 5=Business (non-agricultural products), 6=Salaried employment (formal and informal), 7= Unemployed, 8=Pensioner, 9=Transfer payments, 10=other (specify)…………………

**A2: Provide the following details about the household size**

| Number of adults that livein the household that can still actively engage in production activities | Number of children in household | Total householdsize |
|---|---|---|
| Male...... Females……Total= (from 18 & above) | Males…......Females…(between 0-17years) | Total =…….. |

**A3: Provide the following information about the household power and network connectivity**

| Do you own a phone? 1=Yes, 0=No | Phone type 1=Smart, 2=Analogue | Power connection (CODE C) | Network connectivity(CODE D) |
|---|---|---|---|
| | | | |

**CODE C: Power connection:** 1=Grid (Hydroelectricity power HEP), 2= Connected but off-grid (Solar) 3=Generator, 4=Battery, 5=Wind Power, 6= Not connected to any power source.

**CODE D: Network Stability:** 1=Phone network stable, 2= Phone network unstable

**A4: Provide the following information about property rights**

**A4.1** Do you own land? 1=Yes[ ] 2= No[ ] if **yes** continue, if **no** go to **A4.3**

**A4.1.1** What is the total land owned? ..................

**A4.1.2** What is the type of land tenure of the main land owned by the household? **(CODE E)………………..**

**CODE E:** 1=Owned with title deed, 2=Owned without title deed 3= Rented, 4=Owned by parents 5=Communal/ government/ Cooperative, 6=Borrowed land, 7=Land given for free, 8=Inherited

**A4.2** Do you rent out land? 1=Yes[ ] 2=No[ ] if **yes** continue, if **no** go to **A4.3**

**A4.2.1** What is the total land size rented out? ........acres

**A4.2.2** What is the price per acre of the rented out land per season? ............. Ugx

**A4.3** Do you rent in land? 1=Yes[ ] 2=No [ ] if **yes** continue, if **no** go to **A4.4**

**A4.3.1** If **yes** what is the total land size rented in… ........ acres

**A4.3.2** What is the price per acre of the rented-in land per season.................Ugx?

**A4.4** What is the total land size under general agriculture (in acres

**A4.5** What was the size of land (in acres) under barley production only in the last two seasons?

Season 1 …... Season 2…………

**SECTION B: BARLEY FARMS' CHARACTERISTICS**

**B1.1** How many years of experience do you have in barley production?............. years

**B1.2** Active seasons in the last 12 months? Season 1 [ ] Season 2 [ ] …..

**Adoption status**

**B1.3** Were you an adopter of /registered on BanQu blockchain technology (producing and supplying to NBL buying centres through BCT app) in any of the seasons?

1 (Adopter) =Yes [ ] 2 (Non-adopter) =No [ ], if **Yes** continue, if No go to **B2.1** …

**Season 1 for adopters:**

**B1.4** How many bags (100Kgs size) of barley did you harvest per acre in **Season 1 ...........** bags.

**B1.5** How many bags (100Kgs size) in total did you supply to NBL Company through BCT in **Season 1**? .................... bags

**B1.6** How much did NBL Company buying centre offer you per kilogram of barley in season 1?.....................Ugx

**B1.7** In your opinion, state your level of agreement or disagreement to the following statements regarding the prices you received from NBL through BCT in **Season 1**? (1=strongly disagree, 2=disagree, 3=neutral, 4=agree, 5=strongly agree)

| Statement | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 1) I am happy and satisfied with the price I received per kg of barley supplied to NBL through BCT app | | | | | |

**B1.8** Who was your main input provider for barley production in **Season 1?**

**CODE F:** 1=NBL Company input stores, 2=Middlemen, 3=Agro-input dealer, 4=Exporter, 5= Other farmers, 6=General market, 7=Others (specify)……

**Production and marketing costs incurred by BCT Adopters in Season 1**

**B1.9 Variable costs incurred (Production, Marketing costs) in Season 1:** Provide the following information regarding costs

| **Activity** | **Costs incurred during Season 1 (in Ugx)** |
|---|---|
| Production | |
| Labour for cultivation (both $1^0$ and $2^0$) | |
| Cost of seeds | |
| Cost of fertilizers | |
| Harvesting labour costs | |
| Planting and weeding costs | |
| Others (Specify) | |
| Marketing costs | |
| Transportation costs (to drying grounds, stores/NBL buying centres) | |
| Costs of drying materials | |
| Costs of packing materials costs | |
| Other costs (Specify)…… | |

**Season 2 for BCT adopters:**

**B1.10** How many bags (100Kgs size) of barley did you harvest per acre in **Season 2**………bags.

**B1.11** How many bags (100Kgs size) in total did you supply to NBL Company through BCT in **Season 2**? .................... bags

**B1.12** How much did NBL Company buying centre offer you per kilogram of barley in **season 2**? ..................... Ugx

**B1.13** In your opinion, state your level of agreement or disagreement to the following statements regarding the prices you received from NBL through BCT in **Season 2**? (1=strongly disagree, 2=disagree, 3=neutral, 4=agree, 5=strongly agree)

| Statement | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 1) I am happy and satisfied with the price I received per kg of barley supplied to NBL through BCT app | | | | | |

**B1.14** Who was your main input provider for barley production in **Season 1?**

**<u>CODE F:</u>** 1=NBL Company input stores, 2=Middlemen, 3=Agro-input dealer, 4=Exporter, 5= Other farmers, 6=General market, 7=Others (specify)……

**Production and marketing costs incurred by BCT Adopters in Season 2**

**B1.15 Variable costs incurred (Production, Marketing costs) in Season 2:** Provide the following information regarding costs

| **Activity** | **Costs incurred during Season 2 (in Ugx)** |
|---|---|
| Production | |
| Labour for cultivation (both $1^0$ and $2^0$) | |
| Cost of seeds | |
| Cost of fertilizers | |
| Harvesting labour costs | |
| Planting and weeding costs | |
| Others (Specify) | |
| Marketing costs | |

| | |
|---|---|
| Transportation costs (to drying grounds, stores/NBL buying centres) | |
| Costs of drying materials | |
| Costs of packing materials costs | |
| Other costs (Specify)…… | |

**B1.16** As a BCT adopter, in your opinion state your level of agreement or disagreement to the following statement regarding the ease with which you met production and marketing costs in the last two seasons while producing and supplying through BCT? (1=strongly disagree, 2=disagree, 3=neutral, 4=agree, 5=strongly agree)

| **Statement** | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| 1) With BCT app, I am capable of covering my production and marketing costs with ease | | | | | |

**<u>B2: Non-adopters season 1:</u>**

**B2.1** As a non-adopter of BCT, who was the main buyer of your barley produced in **season 1**?

1=NBL Company buying centres 2=Middlemen

**B2.2** How many bags (100Kgs size) of barley did you harvest per acre in **Season 1**………bags.

**B2.3** How many bags (100Kgs size) in total did you sell to NBL Company/middlemen in **Season 1**?.....................bags

**B2.4** How much did NBL Company buying centre/middlemen offer you per kilogram of barley in **season 1**? ..................... Ugx

**B2.5** Without selling through BCT, in your opinion state the level of agreement or disagreement to the following statements regarding the prices you received from NBL/Middlemen in **Season 1**? (1=strongly disagree, 2=disagree, 3=neutral, 4=agree, 5=strongly agree)

| **Statement** | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| 1) I am happy and satisfied with the price I received per kg of barley sold to NBL | | | | | |
| 2) I am happy and satisfied with the price I received per kg of barley I sold to middlemen | | | | | |

**B2.6** Who was your main input provider for barley production in season 1?

**CODE F:** 1=NBL company stores, 2=Middlemen, 3=Agro-input dealer, 4=Exporter, 5= Other farmers, 6=General market, 7=Others (specify)……

**Production and marketing costs incurred by BCT Non-Adopters in Season 1**

**B2.7 Variable costs incurred (Production, Marketing costs) in Season 1:** Provide the following information regarding costs

| **Activity** | **Costs incurred during Season 1 (in Ugx)** |
|---|---|
| Production | |
| Labour for cultivation (both $1^0$ and $2^0$) | |
| Cost of seeds | |
| Cost of fertilizers | |
| Harvesting labour costs | |
| Planting and weeding costs | |
| Others (Specify) | |
| Marketing costs | |
| Transportation costs (to drying grounds, stores/NBL buying centres) | |
| Costs of drying materials | |
| Costs of packing materials costs | |
| Other costs (Specify)…… | |

**Non-adopters season 2:**

**B2.8** As a non-adopter of BCT, who was the main buyer of your barley produced in **season 2**?

1=NBL Company buying centres 2=Middlemen

**B2.9** How many bags (100Kgs size) of barley did you harvest per acre in **Season 1**………bags.

**B2.10** How many bags (100Kgs size) in total did you supply to NBL Company/sell to in **Season 2**?.....................bags

**B2.11** How much did NBL Company buying centre/middlemen offer you per kilogram of barley in **season 2**? ..................... Ugx

**B2.12** In your opinion, state your level of agreement or disagreement to the following statements regarding the prices you received from NBL buying centres/middlemen in **Season 2**? (1=strongly disagree, 2=disagree, 3=neutral, 4=agree, 5=strongly agree)

| Statement | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 1) I am happy and satisfied with the price I received per kg of barley supplied to NBL | | | | | |

**B2.13** Who was your main input provider for barley production in **Season 2?**

**<u>CODE F:</u>** 1=NBL company stores, 2=Middlemen, 3=Agro-input dealer, 4=Exporter, 5= Other farmers, 6=General market, 7=Others (specify)……

**Production and marketing costs incurred by BCT Non-Adopters in Season 2**

**B2.14 Variable costs incurred (Production, Marketing costs) in Season 1:** Provide the following information regarding costs

| **Activity** | **Costs incurred during Season 2 (in Ugx)** |
|---|---|
| Production | |
| Labour for cultivation (both $1^0$ and $2^0$) | |
| Cost of seeds | |
| Cost of fertilizers | |
| Harvesting labour costs | |
| Planting and weeding costs | |

| | |
|---|---|
| Others (Specify) | |
| Marketing costs | |
| Transportation costs (to drying grounds, stores/NBL buying centres) | |
| Costs of drying materials | |
| Costs of packing materials costs | |
| Other costs (Specify)…… | |

**B2.15** As a BCT non-adopter, in your opinion state the level of agreement or disagreement to the following statements regarding the ease with which you met production and marketing costs in the last two seasons? (1=strongly disagree, 2=disagree, 3=neutral, 4=agree, 5=strongly agree)

| **Statement** | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| 2) Without BCT app, I am capable of covering my production and marketing costs with ease | | | | | |

**B3: Distances to facilities**

**B3.1** What is the distance from the household residential home to the nearest facilities below?

i. NBL buying centre (Km)…………………..…… (Walking mins)…………….....

ii. Main town/trading centre (Km)…………………….. (Walking Mins)……...……...

iii. Barley farm (Km)……...………………(Walking Mins)…………...…

**B3.2** What is the state of the road to NBL buying centre? 1=Tarmac[ ] 2= Murrum[ ]

**SECTION C: BANQU BLOCKCHAIN TECHNOLOGY (BCT) INFORMATION**

**C1** Are you charged for enrolling/registering on BanQu blockchain technology? 1=Yes[ ] 2= No[ ] if **yes** continue, if **no** go to **C3**

**C2** How much did you pay to be enrolled? Ugx …………….

**C3** Is BanQu BCT available for you whenever you wanted to be enrolled? 1=Yes[ ] 2= No[ ]

**C4** Is BanQu BCT compatible with your phone? 1=Yes[ ] 2= No[ ]

**C5** Is there a standard set of guidelines (terms and conditions) followed before enrolling/registering a farmer on BCT?
1=Yes[ ] 2= No[ ] if **yes** continue, if **no** go to **C7**

**C6** Who is the issuing authority of the guideline (terms and conditions)? 1=NBL Company [ ] 2= Government of Uganda through local councils[ ] 3=Other[ ]Specify…………

**C7** After registering on BCT, in case a farmer does not comply with the agreed terms and conditions (such as failure to supply the produce to NBL), is there a set of rules and procedures for handling non-compliance?
1=Yes[ ] 2= No (NBL makes a loss)[ ] if **yes** continue, if **no** go to **C9**

**C8** Who is the issuing authority of the rules and procedures that handle non-compliance? 1=NBL Company [ ] 2= Government of Uganda through local councils[ ] 3=Other[ ]Specify…………………..

**C9** Is there any form of penalty given for non-compliance? 1=Yes [ ] 2= No[ ] if **yes** continue, if **no** go to **C11**

**C10** What form of penalty is given for non-compliance with the terms and conditions?
1=Withholding BCT[ ] 2=Issue handled mutually between NBL and the farmer[ ] 3= Issue handled formally in courts of law [ ] 4= Others [ ]Specify……………

**C11** Is farmer enrolment on BCT voluntary? 1=Yes[ ] 2= No[ ] if **yes** go to **Section D**, if **no** continue

**C12** Are there formal legal procedures for handling farmers who refuse to sign up for BCT?? 1=Yes[ ] 2= No[ ] if **yes** continue, if **no** go to **Section D**

**C13** Who is the issuing authority of the legal procedures that handle farmers who refuse to sign up for BCT? 1=NBL Company [ ] 2= Government of Uganda through local councils[ ] 3=Other[ ]Specify…………………..

## SECTION D: ACCEPTANCE OF BLOCKCHAIN TECHNOLOGY

**Socio-psychological factors**

**D1:** In your opinion, state your level of agreement or disagreement to the following statements regarding your perception towards accepting blockchain technology (1=strongly disagree, 2=disagree, 3=neutral, 4=agree, 5=strongly agree) (**SA**=strongly disagree, **D**=disagree, N=neutral, **A**=agree, **SA**=strongly agree)

| **Statement** | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| **Subjective (SUN)** | | | | | |
| SUN1. I think that people important to me (like friends) would want me to use BCT | | | | | |
| SUN2. I think that my family members consider BCT to be a good innovation for me to accept and adopt | | | | | |
| SUN3. I think that other fellow barley farmers would want me to accept and adopt BCT | | | | | |
| SUN4. I think that my use of BCT would be supported by other stakeholders like NBL staff at all levels | | | | | |
| SUN5. I think that my use of BCT would be supported by the government of Uganda and all local authorities | | | | | |
| **Farmer attitude (FA)** | | | | | |
| FA1. I have a positive feeling regarding the use of BCT in my barley VC activities | | | | | |
| FA2. I like using BCT app in my barley VC activities | | | | | |
| FA3. Using BCT in my barley VC operations is a good idea | | | | | |
| FA4. Until now, I admire the use of BCT app in my barley VC activities | | | | | |
| FA5. I am satisfied and happy for using BCT app in my barley VC operations | | | | | |
| **Farmer Image (FI)** | | | | | |
| FI1. Using BCT enhances my status/respect among my fellow farmers and in the society | | | | | |

| | | | | | |
|---|---|---|---|---|---|
| FI2. I feel special for using BCT in my barley production and supply activities | | | | | |
| FI3. Farmers that use BCT app have more prestige in society than those farmers who do not | | | | | |
| FI4. Farmers that use BCT are usually associated with high profile | | | | | |
| FI5. Generally using BCT app is a status symbol in our society | | | | | |
| **BCT relevance to barley VC (BR)** | | | | | |
| BR1. BCT makes it easy for me to access inputs from NBL input stores | | | | | |
| BR2. BCT use eliminates price exploitation by middlemen and NBL company | | | | | |
| BR3. BCT improves trust among the actors (farmers, and NBL staff) in the barley VC | | | | | |
| BR4. BCT makes my payments after supply to NBL easy (less worrisome) | | | | | |
| BR5. BCT makes me recognized in the barley VC because of the messages that I get | | | | | |
| **Barley output quality (BQ)** | | | | | |
| BQ1. Because I get good seeds from NBL through BCT, the quality of my barley is usually good | | | | | |
| BQ2. Because I have access to other inputs like fertilizers, packaging materials etc. through BCT, the quality of my output is usually good | | | | | |
| BQ3. Through BCT, I am able to access regular information regarding enhancing barley production quality | | | | | |
| BQ4. The use of BCT reduces the likelihood of rejections of my barley at NBL buying centres | | | | | |
| BQ5. Overall, the use of BCT enhances the overall quality attributes of my barley | | | | | |
| **BCT result demonstrability (BD)** | | | | | |
| BD1. I have no difficulty telling others about the results of using BCT app in my barley VC activities | | | | | |
| BD2. The results of using BCT in my barley VC activities are clear and visible to me and everyone else | | | | | |

| | | | | | |
|---|---|---|---|---|---|
| BD3. I believe I could communicate to other people the results of using BCT | | | | | |
| BD4. It is (difficult not to notice) easy to notice the benefits of using BCT app in barley VC activities | | | | | |
| **Voluntariness in accepting BCT (VB)** | | | | | |
| BV1. NBL Company staff does not force me to use BCT app | | | | | |
| BV2. The local authorities/government of Uganda does not force me to use BCT app | | | | | |
| BV3. My fellow farmers (farmers in the same farmer groups) do dot force me to register on BCT app | | | | | |
| BV4. It is not a mandatory requirement from the stakeholders in the barley VC for me to use BCT | | | | | |
| BV5. Despite BCT app advantages, it is my free will to use it or not | | | | | |
| **Perceived usefulness of BCT (PU)** | | | | | |
| PU1. I believe that using BCT improves my barley productivity | | | | | |
| PU2. I believe that using BCT increases my gross margin | | | | | |
| PU3. I believe that use of BCT reduces my transaction costs especially during marketing | | | | | |
| PU4. I find the use of BCT to be effective in reducing my overall costs of production | | | | | |
| PU5. Overall, I find the use of BCT app in barley VC operations very useful | | | | | |
| **Perceived ease of use (PEU)** | | | | | |
| PEU1. BCT app is easy to use on my phone | | | | | |
| PEU2. BCT app is simple and easily understandable. | | | | | |
| PEU3. The training process of learning how to use BCT was easy and smooth | | | | | |
| PEU4. It is easy to get my transaction statements or check them on BCT app whenever I need to | | | | | |
| PEU5. Generally, the use of BCT does not require a lot of my mental input/effort | | | | | |

| | | | | | |
|---|---|---|---|---|---|
| **Perceived behavioural control (PBC)** | | | | | |
| PBC1. I have what it takes (ownership of a phone) to use BanQu BCT software app | | | | | |
| PBC2. I have easy access to a power source for charging my phone any time it runs out of battery | | | | | |
| PBC3. I have good network connectivity on my phone which enables me to use BanQu BCT app | | | | | |
| PBC4. I have access to training regarding the use of BanQu BCT app | | | | | |
| PBC5. Overall, I have the necessary skills to interact with and use BCT app during barley VC operations | | | | | |
| **Behavioural intention to accept BCT (BI)** | | | | | |
| BI1. I intend to use BCT in my barley production activities in the future | | | | | |
| BI2. I predict I would use BCT in my barley supply activities in the future | | | | | |
| BE3. I will recommend the use of BCT to other farmers | | | | | |
| BE4. Given opportunity, I would produce and supply through BCT app throughout | | | | | |
| **Use of BCT (AUB)** | | | | | |
| AUB1. I am using BCT in my barley value chain activities | | | | | |
| AUB2. I used BCT in all barley growing seasons from its introduction to date | | | | | |
| AUB3. I used BCT app rarely (in some of the growing seasons) in my barley VC activities | | | | | |
| **Injunctive Norm (IN)** | | | | | |
| IN1. My family approves of me using BCT | | | | | |
| IN2. My fellow barley farmers think that I should use BCT | | | | | |
| IN3. My family and fellow farmers subject me on pressure to use BCT | | | | | |
| IN4. NBL staff at all levels would want me to use BCT | | | | | |

| | | | | | |
|---|---|---|---|---|---|
| IN5. The local government authorities and agricultural officers approve of me and others using BCT | | | | | |
| **Normative reference groups (NRG)** | | | | | |
| NRG1. The NBL extension staff registered most of the farmers in my sub-county so I think that I should also get enrolled/registered BCT | | | | | |
| NRG2. The Agricultural extension officers in my sub-county encourage me and other farmers to use BCT | | | | | |
| NRG3. The local council authorities in my village/parish would want me and others to use BCT | | | | | |
| NRG4. When it comes to use of BCT, I want to be like my fellow farmers in my village who use BCT | | | | | |
| NRG5. Most progressing farmers and farmer groups are registered on BCT so I should also get registered on it | | | | | |
| **Behavioural sanctions (BS)** | | | | | |
| BS1. My fellow farmers would associate with me freely if use BCT just like them | | | | | |
| BS2. If I do not use BCT, my fellow farmers would think less of me | | | | | |
| BS3. I feel embarrassed/out of place among my farmer friends who use BCT, for not using BCT | | | | | |
| BS4. During field extension meetings, I would want to be accepted by NBL field staff because of using BCT | | | | | |
| BS5. I do not want to feel left behind by my fellow farmers due to not using BCT | | | | | |

## SECTION E: ADOPTION AND EXTENT OF USE OF BLOCKCHAIN TECHNOLOGY (for adopters only)

### E1: Blockchain related training, and Credit access.

**E1.1** Did you receive any BCT related training prior or after adoption/registering? 1=Yes[ ] 2= No [ ] if **yes** continue, if **no** go to **E2**

**E1.2** How many times did you receive BCT related training in the last 12 months? ....................

**E1.3** Did you incur any cost in getting BCT related training? 1=Yes [ ] 2=No [ ] if **yes** continue, if **no** go to **E2**

**E1.4** What type of cost did you incur? 1=transport cost of NBL staff [ ] 2=time spent[ ] 3=payment for the training received 4=others (specify)……..

**E1.5** Please provide the amount of money incurred in costs for obtaining BCT related training in **Ugx……**

| **Type of extension service cost** | **Cost in Ugx** |
|---|---|
| Transport cost of NBL staff | |
| Time spent (amount earned if worked) | |
| Payment for the training received | |
| Others (specify)………………. | |

**E2: Agricultural extension services information**

E2.1 Did you receive agricultural extension services in the last 12 months? 1=Yes[ ] 2= No[ ] if **yes** continue, if **no** go to **E3**

**E2.2** How frequent was the extension service? 1=weekly[ ] 2=Monthly[ ] 3=seasonally (once per season) [ ] 4= annually (once a year) [ ] 5=More than twice a year[ ]

**E2.3** What is the mode of extension delivery? 1=Farm visits[ ] 2=Field days[ ] 3=Office visits[ ] 4=Demonstrations [ ], 5=Seminars/trainings [ ], 5=others (specify)……………….

**E2.4** Are the extension services always available when you need help? 1=Yes [ ] 2=No [ ]

**E2.5** Which extension service providers did you engage with?...1=Government extension officers [ ] 2=NBL extension staff [ ] 3=NGOs [ ] 4=Farmer groups[ ] 5=Specify others if any…..........?

**E2.6** What services were you provided with by the extension officers? 1 =Marketing information[ ] 2=Agronomic practices [ ] 3= Postharvest handling practices 4=Quality management 5=others (specify) ……………

**E2.7** Did you incur any cost in getting extension service? 1=Yes [ ] 2=No [ ] if **yes** continue, if **no** go to **E3**

**E2.8** What type of cost did you incur? 1=transport cost to an extension officer [ ] 2=time spent[ ] 3=payment for the extension service 4=others (specify)……..

**E2.9** Please provide the amount of money incurred in costs for obtaining any of the extension services in **Ugx**

| **Type of extension service cost** | **Cost in Ugx** |
|---|---|
| Transport cost to agricultural extension officer | |
| Time spent (amount earned if worked) | |
| Payment for the extension service received | |
| Others (specify)….. | |

**E2.10** How do you agree with the following statement? Extension service providers can be trusted when it comes to farming information provision. 1= strongly disagree[ ] 2= disagree [ ] 3= neutral [ ] 4= agree [ ] 5=strongly agree [ ]

**E3: Access to credit services**

**E3.1** Did you ever need credit during the last two barley production seasons? 1=Yes [ ] 2=No [ ] If **yes** continue, if **no** go to **E4**

**E3.2** Did you apply for any credit in the last two barley production seasons? 1=Yes [ ] 2=No [ ] If **yes** continue, if **no** go to **E3.13**

**E3.3** Did you get the credit? 1=Yes [ ] 2=No [ ] If **yes** continue, if **no** go to **E3.12**

**E3.4** Did you get the whole amount applied/requested for? 1=Yes [ ] 2=No [ ] If **yes** go to **E3.6** if **No** continue.

**E3.5** Why were you not given the whole amount? 1=had an outstanding loan [ ] 2=had no security [ ] 3=others (specify

**E3.6** What was the source of your credit? You can tick more than one source

**<u>Source of credit</u>**

1= NBL Company [ ] 2= Loan from family/friends/neighbour [ ] 3= Loan from a SACCO [ ] 4= Commercial Banks [ ]

5= Mobile money loan such as MTN Mocash or Airtel Beraako [ ] 6= Loan from a microfinance [ ] 7= Loan from an informal moneylender [ ] 8= Farmer group cash rounds [ ] 9= Loan/credits from barley traders (middlemen) [ ] 10= Others [ ] please specify)…………………

**E3.7** Please indicate the amount of cash credit received in Ugx.

| **Source of credit** | **Amount received (Ugx)** |
|---|---|
| 1=NBL Company | |
| 2= Loan from family/friends/neighbour | |
| 3= Loan from a SACCO | |
| 4= Commercial Banks | |
| 5= Mobile money loan such as MTN Mocash or Airtel Beraako | |
| 6= Loan from a microfinance | |
| 7= Loan from an informal moneylender | |
| 8= Farmer group cash rounds | |
| 9= Loan/credits from barley traders (middlemen) | |
| 10= Others (Specify)…….. | |

**E3.8** Was the credit given in cash or in kind? 1=in cash [ ] 2=in kind [ ]. If in cash continue, if in kind go to **E3.10**

**E3.9** Which activities did you use cash credit for? You can tick more than one activity

1=Purchase inputs like seeds, fertilizers, packing and drying materials [ ] 2=Hiring human labor [ ] 3=Hiring mechanical/animal labour [ ], 4= Purchase of machinery or draught animals [ ] 5=Use in non-barley production activities

**E3.10** In what kinds did you receive the credit? 1=Seeds [ ] 2=Fertilizers [ ] 3=Packing materials [ ] 4=Drying materials [ ]

Others [ ] (specify)……….

**E3.11** How did you repay the credit? 1=by selling barley [ ] 2=from other sources [ ]

**E3.12** What was the reason for not being given? 1=had an outstanding loan [ ] 2=had no security [ ] 3=Poor credit history [ ] 4=Others [ ] (specify)……

**E3.13** Why did you not apply for credit? 1=fear [ ] 2=expensive [ ] 3=had no security[ ] 4=Lack of knowledge [ ] 5= Others [ ] (specify)……….

**E4. Social capital**

**E4.1** Do you belong to any group association? 1=Yes [ ] 2=No [ ] If **yes** continue, if **no** go to question **E4.5**

**E4.2** Which type of group association do you belong to? 1=Conventional farmer group [ ] 2=Barley growers cooperative [ ] 3=Welfare group [ ] 4=Cash rounds group [ ] 6=others (specify)………………

**E4.3** How long have you been a member of a group association? ................ months/years

**E4.4** What benefits do you derive from group membership? 1=access to barley production information [ ] 2=advice on barley production and management practices [ ]3=information on credit access [ ] 4= market information 5=welfare [ ]
6=others [ ] (specify) ………….

**E4.5** Why don't you belong to a group? 1=high membership fee [ ]2=Long distance between group members [ ] 3=lack of trust [ ] 4=others [ ] (specify………

**<u>SECTION G: CHALLENGES IMPEDING BLOCKCHAIN TECHNOLOGY IMPLEMENTATION</u>**

G1 From the following list, provide a tick in front of the statements if in your opinion, it qualifies as a challenge hindering BCT implementation in your district/village

| **Statement** | ✓ |
|---|---|
| 1) BCT is complex for me (and other farmers) to use or understand | |

| | |
|---|---|
| 2) BCT is in most cases not compatible with my phone or most phones of other farmers | |
| 3) BCT is expensive for me to have since its initial and maintenance cost is high | |
| 4) My and other farmers' attitude is negative towards BCT use | |
| 5) Most farmers do not have phones making it difficult for them to use BCT | |
| 6) NBL Company does not have adequate funds to sustain the use of BCT in this region | |
| 7) NBL Company has limited number of knowledgeable field staff to train, and enrol farmers on BCT | |
| 8) I and other farmers have limited knowledge regarding the use of BCT | |
| 9) NBL Company staff are not cooperative when it comes to enrolling farmers on BCT | |
| 10) NBL Company's top managers do not support and are not committed to use of BCT in the barley VC | |
| 11) The middlemen oppose the use of BCT because they fear to lose their business and their profits | |
| 12) There are no clear guidelines from the government regarding the implementation of BCT in barley VC | |
| 13) When farmers enrolled on BCT refuse to supply to NBL, there are no rules and procedures to handle them | |
| 14) Being a new technology, farmers as well as NBL company fear the uncertainty of BCT's future consequences | |
| 15) Others (Specify)…………….. | |

G2 In your opinion, suggest solutions for the above selected BCT implementation challenges in your Parish

……………………………………………………………………………………………………………………………………

***Thank you***

GPS ccordinates……………… Time finished: ……………

**Appendix B: Pair-wise comparison matrices to collect data during group discussions and key informant interviews**

**EGERTON UNIVERSITY**

**Part A**

1. Welcoming participant(s)
2. Introduction of the facilitator and note taker
3. Explaining the purpose of the discussion/meeting
4. Explaining how the prioritization will be done using an example
5. Assuring confidentiality and seeking for consent from the participant(s) (consent forms signed)

**Part B**

1. Demographics of the participants

| Pseudo name | Sex | Marital status | Age | Education level | Barley growing experience |
|---|---|---|---|---|---|
| | | | | | |

**Part C**

**Presenting the pair-wise comparison matrices to the participant(s) and explaining how it is filled**

**<u>PAIRWISE COMPARISON MATRICES</u>**

This matrix has two parts; part 1 is about the challenges and sub-challenges, while part 2 is about suggesting solutions

**1.** Rate the challenges in the table below depending **on the level of importance (their criticality)** you attach to them. **Key to rating the challenge importance: 1-** Equal importance; **3-** Moderate importance; **5-** Strong importance; **7-** Very strong importance; **9-** Extreme importance; **2,4,6,8** are intermediate values.

**NOTE:**

1. The categorization of priority challenges and their sub-challenges were derived from intense worldwide literature review of earlier user cases of BCTs in different firms/companies, sectors, and countries. Examples of such literature: (Kshetri, 2021; Mohammad Saif *et al*., 2022; Mohanta *et al.*, 2020; Nzau, 2023; Queiroz & Fosso Wamba, 2019; Yadlapalli *et al*., 2022).
2. Follow the example given below to assign rates as agreed upon in the groups (for group discussions) / as an individual (for KIs)

| **1. Question regarding challenge categories** | **Rate** |
|---|---|
| **BCT Technology based challenge category compared to all** | |
| ***Example:*** *How important is technological challenge with respect to farmer-based challenge? (Rating it **3** means that BCT technological challenge category is 3 times more critical than farmer-based challenge category)* | **3** |
| How important is BCT technological challenge with respect to farmer-based challenge? | |
| How important is BCT technological challenge with respect to Company B (NBL company) based challenge? | |
| How important is BCT technological challenge with respect to middlemen/agents-based challenge? | |
| How important is BCT technological challenge with respect to regulatory based challenge? | |
| **Farmer based challenge category compared to all** | |
| How important is farmer-based challenge with respect to Company B (NBL company) based challenge? | |
| How important is farmer-based challenge with respect to middlemen-based challenge? | |
| How important is farmer-based challenge with respect to regulatory based challenge? | |
| **Company B (NBL) based challenge category compared to all** | |
| How important is Company B (NBL Company) based challenge with respect to middlemen/Agents based challenge? | |
| How important is Company B (NBL Company) based challenge with respect to regulatory based challenge? | |
| **Middlemen/agents-based challenge category compared to all** | |
| How important is middlemen/agents-based challenge with respect to regulatory based challenge? | |
| **1.2. Question regarding challenge category attributes/sub-challenges** | |

| | |
|---|---|
| **BCT challenge category attributes (sub-challenges) compared to all other sub-challenges** | |
| How important is BCT complexity challenge with respect to farmer’s phone compatibility challenge? | |
| How important is BCT complexity challenge with respect to initial cost of BCT challenge? | |
| How important is BCT compatibility challenge with respect to initial cost of BCT challenge? | |
| **Farmer based challenge category attributes (sub-challenges) compared to all other sub-challenges** | |
| How important is farmer’s negative attitude towards BCT challenge with respect to a famer not owning a phone challenge? | |
| How important is farmer’s negative attitude towards BCT challenge with respect to a famer having limited knowledge regarding BCT? | |
| How important is farmer’s negative attitude towards BCT challenge with respect to no loyalty/trust from farmers to Company B? | |
| How important is famer not owning a phone challenge with respect famer having limited knowledge regarding BCT? | |
| How important is famer not owning a phone challenge with respect to no loyalty/trust from farmers to Company B? | |
| How important is challenge famer having limited knowledge regarding BCT with respect to no loyalty/trust from farmers to Company B? | |
| **Company B (NBL) challenge category attributes (sub-challenges) compared to all other sub-challenges** | |
| How important is Company B (NBL’s) limited financial resources challenge with respect to inadequate Company B’s (NBL’s) top management support and commitment towards BCT challenge? | |
| How important is Company B (NBL’s) limited financial resources to sustain BCT challenge with respect to inadequate BCT knowledge of some Company B (NBL) staff challenge? | |
| How important is inadequate Company B’s (NBL’s) top management support and commitment towards BCT challenge with respect to inadequate BCT knowledge of some company B’s (NBL’s) staff challenge? | |
| **Regulatory based challenge category attributes (sub-challenges) compared to all other sub-challenges** | |

| | |
|---|---|
| How important is absence of clear BCT implementation guidelines sub-challenge with respect to absence of rules and regulation for non-complying farmers sub-challenge? | |
| How important is absence of clear BCT implementation guidelines sub-challenge with respect to lack of and or inadequate support from government local council authorities (like chairman 1, councillors, and government extension agents) sub-challenge? | |
| How important is absence of rules and regulation for non-complying farmers sub-challenge with respect to lack of and or inadequate support from government local council authorities (like chairman 1, councillors, and government extension agents) sub-challenge? | |
| **Middlemen based challenge category attributes (sub-challenges) compared to all other sub-challenges** | |
| How important is middlemen/agent's fear of losing business sub-challenge with respect to absence of a clear rewarding strategy to middlemen/agents for the supply (barley) collected and delivered on behalf of the farmer to Company B (NBL) buying centres sub-challenge? | |

**Part 1 Pair-wise comparison matrices for data collection**

**Pair-wise comparison matrix for challenge categories**

| | Technology based | Farmer based | Company B-based | Middlemen based | Regulatory based |
|---|---|---|---|---|---|
| Technology based | 1 | | | | |
| Farmer Based | | 1 | | | |
| Company B-based | | | 1 | | |
| Middlemen based | | | | 1 | |
| Regulatory based | | | | | 1 |

**Technology based category attributes pair-wise comparison matrix**

| | **Complexity** | Compatibility | **Initial cost** |
|---|---|---|---|
| Complexity | **1** | | |
| Compatibility | | **1** | |
| Initial cost | | | **1** |

**Farmer based category attributes pair-wise comparison matrix**

| | Negative attitude | No phone owned | Limited knowledge | Limited trust/loyalty |
|---|---|---|---|---|
| Negative attitude | **1** | | | |
| No phone owned | | **1** | | |
| Limited knowledge | | | **1** | |
| Limited trust/loyalty | | | | **1** |

**Company B Company based category attributes pair-wise comparison matrix**

| | Limited financial resources | Inadequate top management support | Staff limited knowledge of BCT |
|---|---|---|---|
| Limited financial resources | 1 | | |
| Inadequate top management support | | 1 | |
| Staff limited knowledge of BCT | | | 1 |

**Regulatory based category attributes pair-wise comparison matrix**

| | No clear guidelines | No rules for non-complying farmers | Inadequate government support |
|---|---|---|---|
| No clear guidelines | **1** | | |
| No rules for non-complying farmers | | **1** | |
| Inadequate government support | | | **1** |

**Part 2. Suggest solutions for each of the challenges as rated above**

| **Challenge Category** | **Solution** |
|---|---|
| Technology based | |
| Farmer based | |
| Company B based | |
| Middlemen based | |
| Regulatory based | |

***Thank you***

# Appendix C: Results of the double hurdle model (DHM) using Craggit command

```
. craggit BCTadopt sex Age schooling_Year marital_status Extension_Frequency freq_BCTtraining belong_group BCT
> train_cost Network_Connection_02 prod_costs Power_Connection_03 Land_Tenure_03 NBLbuying_centre_KM landsize_
> own BCT_initial_cost BCTcompat Extension_costs marketing_costs Owned_Phone ,second( numberof_seasons sex Age
>  schooling_Year marital_status Extension_Frequency freq_BCTtraining belong_group BCTtrain_cost Network_Conne
> ction_02 prod_costs Power_Connection_03 Land_Tenure_03 NBLbuying_centre_KM landsize_own BCT_initial_cost Ext
> ension_costs marketing_costs Owned_Phone) vce(robust) nolog

Estimating Cragg's tobit alternative
Assumes conditional independence
initial:       log pseudolikelihood =     -<inf>  (could not be evaluated)
feasible:      log pseudolikelihood = -6734.2384
rescale:       log pseudolikelihood = -1428.4755
rescale eq:    log pseudolikelihood = -618.73135

                                                  Number of obs =       490
                                                  Wald chi2(19) = 14928.24
Log pseudolikelihood = -202.65155                 Prob > chi2   =   0.0000
```

| | Coefficient | Robust std. err. | z | P>\|z\| | [95% conf. | interval] |
|---|---|---|---|---|---|---|
| **Tier1** | | | | | | |
| sex | .0854891 | .2599316 | 0.33 | 0.742 | -.4239676 | .5949457 |
| Age | -.0087242 | .0065093 | -1.34 | 0.180 | -.0214822 | .0040338 |
| schooling_Year | .0173035 | .0173302 | 1.00 | 0.318 | -.0166631 | .05127 |
| marital_status | -3.105226 | .6549261 | -4.74 | 0.000 | -4.388858 | -1.821595 |
| Extension_Frequency | -.2107299 | .0539716 | -3.90 | 0.000 | -.3165123 | -.1049474 |
| freq_BCTtraining | 5.931999 | .1034075 | 57.37 | 0.000 | 5.729324 | 6.134674 |
| belong_group | -.2090458 | .1745043 | -1.20 | 0.231 | -.551068 | .1329763 |
| BCTtrain_cost | -.0003772 | .0000278 | -13.55 | 0.000 | -.0004318 | -.0003226 |
| Network_Connection_02 | 3.314731 | .4945346 | 6.70 | 0.000 | 2.345461 | 4.284001 |
| prod_costs | 3.98e-07 | 1.88e-07 | 2.12 | 0.034 | 3.04e-08 | 7.66e-07 |
| Power_Connection_03 | .0835549 | .178834 | 0.47 | 0.640 | -.2669533 | .434063 |
| Land_Tenure_03 | -.7729772 | .2987934 | -2.59 | 0.010 | -1.358602 | -.1873528 |
| NBLbuying_centre_KM | -.0451494 | .0220534 | -2.05 | 0.041 | -.0883733 | -.0019255 |
| landsize_own | .1120044 | .0469859 | 2.38 | 0.017 | .0199138 | .204095 |
| BCT_initial_cost | -.0023812 | .0004699 | -5.07 | 0.000 | -.0033022 | -.0014602 |
| BCTcompat | 10.37776 | .3537005 | 29.34 | 0.000 | 9.684517 | 11.071 |
| Extension_costs | -1.77e-06 | 2.26e-06 | -0.78 | 0.434 | -6.20e-06 | 2.66e-06 |
| marketing_costs | -1.37e-06 | 6.21e-07 | -2.21 | 0.027 | -2.59e-06 | -1.54e-07 |
| Owned_Phone | 1.422152 | .5280234 | 2.69 | 0.007 | .3872453 | 2.457059 |
| _cons | -7.257821 | .6615716 | -10.97 | 0.000 | -8.554478 | -5.961165 |
| **Tier2** | | | | | | |
| sex | .2496727 | .1413639 | 1.77 | 0.077 | -.0273953 | .5267408 |
| Age | .0114795 | .0038683 | 2.97 | 0.003 | .0038977 | .0190613 |
| schooling_Year | .0235857 | .0105765 | 2.23 | 0.026 | .0028562 | .0443152 |
| marital_status | .2651991 | .2076421 | 1.28 | 0.202 | -.1417719 | .6721701 |
| Extension_Frequency | .0579478 | .0355427 | 1.63 | 0.103 | -.0117147 | .1276103 |
| freq_BCTtraining | .1852887 | .043439 | 4.27 | 0.000 | .1001499 | .2704275 |
| belong_group | .2141277 | .0794843 | 2.69 | 0.007 | .0583414 | .369914 |
| BCTtrain_cost | .0000518 | 7.47e-06 | 6.93 | 0.000 | .0000371 | .0000664 |
| Network_Connection_02 | .0838428 | .0980736 | 0.85 | 0.393 | -.1083779 | .2760636 |
| prod_costs | -9.30e-08 | 9.50e-08 | -0.98 | 0.328 | -2.79e-07 | 9.32e-08 |
| Power_Connection_03 | .1608215 | .1372075 | 1.17 | 0.241 | -.1081002 | .4297432 |
| Land_Tenure_03 | .0721947 | .075692 | 0.95 | 0.340 | -.0761589 | .2205484 |
| NBLbuying_centre_KM | -.0239299 | .0114044 | -2.10 | 0.036 | -.0462821 | -.0015778 |
| landsize_own | -.0389275 | .0178605 | -2.18 | 0.029 | -.0739334 | -.0039215 |
| BCT_initial_cost | -.0005889 | .0002712 | -2.17 | 0.030 | -.0011205 | -.0000573 |
| Extension_costs | 6.14e-07 | .0000127 | 0.05 | 0.961 | -.0000243 | .0000255 |
| marketing_costs | 1.91e-07 | 5.47e-07 | 0.35 | 0.727 | -8.80e-07 | 1.26e-06 |
| Owned_Phone | -.2458692 | .2718416 | -0.90 | 0.366 | -.778669 | .2869305 |
| _cons | 2.663543 | .4159353 | 6.40 | 0.000 | 1.848325 | 3.478761 |
| **sigma** | | | | | | |
| _cons | .5552063 | .0250894 | 22.13 | 0.000 | .506032 | .6043807 |

## Estimates of the marginal effects (dy/dx) after craggit

```
. margins, dydx(_all)

Average marginal effects                              Number of obs = 490
Model VCE: Robust

Expression: Linear prediction, predict()
dy/dx wrt:  sex Age schooling_Year marital_status Extension_Frequency freq_BCTtraining belong_group
            BCTtrain_cost Network_Connection_02 prod_costs Power_Connection_03 Land_Tenure_03
            NBLbuying_centre_KM landsize_own BCT_initial_cost BCTcompat Extension_costs marketing_costs
            Owned_Phone
```

| | dy/dx | Delta-method std. err. | z | P>\|z\| | [95% conf. | interval] |
|---|---|---|---|---|---|---|
| sex | .0854891 | .2599316 | 0.33 | 0.742 | -.4239676 | .5949457 |
| Age | -.0087242 | .0065093 | -1.34 | 0.180 | -.0214822 | .0040338 |
| schooling_Year | .0173035 | .0173302 | 1.00 | 0.318 | -.0166631 | .05127 |
| marital_status | -3.105226 | .6549261 | -4.74 | 0.000 | -4.388858 | -1.821595 |
| Extension_Frequency | -.2107299 | .0539716 | -3.90 | 0.000 | -.3165123 | -.1049474 |
| freq_BCTtraining | 5.931999 | .1034075 | 57.37 | 0.000 | 5.729324 | 6.134674 |
| belong_group | -.2090458 | .1745043 | -1.20 | 0.231 | -.551068 | .1329763 |
| BCTtrain_cost | -.0003772 | .0000278 | -13.55 | 0.000 | -.0004318 | -.0003226 |
| Network_Connection_02 | 3.314731 | .4945346 | 6.70 | 0.000 | 2.345461 | 4.284001 |
| prod_costs | 3.98e-07 | 1.88e-07 | 2.12 | 0.034 | 3.04e-08 | 7.66e-07 |
| Power_Connection_03 | .0835549 | .178834 | 0.47 | 0.640 | -.2669533 | .434063 |
| Land_Tenure_03 | -.7729772 | .2987934 | -2.59 | 0.010 | -1.358602 | -.1873528 |
| NBLbuying_centre_KM | -.0451494 | .0220534 | -2.05 | 0.041 | -.0883733 | -.0019255 |
| landsize_own | .1120044 | .0469859 | 2.38 | 0.017 | .0199138 | .204095 |
| BCT_initial_cost | -.0023812 | .0004699 | -5.07 | 0.000 | -.0033022 | -.0014602 |
| BCTcompat | 10.37776 | .3537005 | 29.34 | 0.000 | 9.684517 | 11.071 |
| Extension_costs | -1.77e-06 | 2.26e-06 | -0.78 | 0.434 | -6.20e-06 | 2.66e-06 |
| marketing_costs | -1.37e-06 | 6.21e-07 | -2.21 | 0.027 | -2.59e-06 | -1.54e-07 |
| Owned_Phone | 1.422152 | .5280234 | 2.69 | 0.007 | .3872453 | 2.457059 |

# Appendix D: Estimation results of ESR model for productivity function

```
. movestay ln_Barley_Productivity Main_occupation_1 sex Seeds_per_acre Fertilizer_per_acre labour_per_acre barle
> y_expereince_01 Age Household_labour Land_Tenure_01 landsize_own Schooling_Year ln_NBLbuying_centre_Mins Dista
> nce_barleyfarm_Mins, select( BCTadopt = receive_BCTtraining_02 belong_group_01 ) nolog


Fitting initial values .....
Endogenous switching regression model           Number of obs    =        491
                                                Wald chi2(13)    =      44.33
Log likelihood = -334.32042                     Prob > chi2      =     0.0000
```

| | Coefficient | Std. err. | z | P>\|z\| | [95% conf. | interval] |
|---|---|---|---|---|---|---|
| **ln_Barley_Productivity_1** | | | | | | |
| Main_occupation_1 | -.0081497 | .0995037 | -0.08 | 0.935 | -.2031734 | .186874 |
| sex | -.1552788 | .0637037 | -2.44 | 0.015 | -.2801357 | -.0304218 |
| Seeds_per_acre | .001097 | .0012561 | 0.87 | 0.382 | -.001365 | .0035589 |
| Fertilizer_per_acre | -.0006108 | .0012254 | -0.50 | 0.618 | -.0030124 | .0017909 |
| labour_per_acre | .0016914 | .0020726 | 0.82 | 0.414 | -.0023707 | .0057536 |
| barley_expereince_01 | -.0301234 | .0069773 | -4.32 | 0.000 | -.0437986 | -.0164482 |
| Age | .0027712 | .0027591 | 1.00 | 0.315 | -.0026366 | .008179 |
| Household_labour | .0193871 | .0130948 | 1.48 | 0.139 | -.0062782 | .0450525 |
| Land_Tenure_01 | -.0073539 | .0432345 | -0.17 | 0.865 | -.092092 | .0773842 |
| landsize_own | -.0181603 | .0101684 | -1.79 | 0.074 | -.03809 | .0017694 |
| Schooling_Year | -.004883 | .006217 | -0.79 | 0.432 | -.0170682 | .0073021 |
| ln_NBLbuying_centre_Mins | .1037285 | .0251346 | 4.13 | 0.000 | .0544656 | .1529914 |
| Distance_barleyfarm_Mins | -.0008191 | .0034586 | -0.24 | 0.813 | -.0075979 | .0059596 |
| _cons | 6.958821 | .2164008 | 32.16 | 0.000 | 6.534683 | 7.382959 |
| **ln_Barley_Productivity_0** | | | | | | |
| Main_occupation_1 | -.0195465 | .0944575 | -0.21 | 0.836 | -.2046797 | .1655867 |
| sex | -.0490946 | .0911532 | -0.54 | 0.590 | -.2277516 | .1295624 |
| Seeds_per_acre | .0097129 | .0017034 | 5.70 | 0.000 | .0063742 | .0130516 |
| Fertilizer_per_acre | .0004251 | .0019294 | 0.22 | 0.826 | -.0033565 | .0042067 |
| labour_per_acre | .0067596 | .0033139 | 2.04 | 0.041 | .0002645 | .0132547 |
| barley_expereince_01 | -.0244359 | .0092409 | -2.64 | 0.008 | -.0425478 | -.0063241 |
| Age | -.0033689 | .0028882 | -1.17 | 0.243 | -.0090297 | .002292 |
| Household_labour | -.0003595 | .0170828 | -0.02 | 0.983 | -.0338412 | .0331221 |
| Land_Tenure_01 | .1953451 | .0502149 | 3.89 | 0.000 | .0969257 | .2937644 |
| landsize_own | .0073012 | .013137 | 0.56 | 0.578 | -.0184469 | .0330493 |
| Schooling_Year | -.0223345 | .0075627 | -2.95 | 0.003 | -.0371572 | -.0075118 |
| ln_NBLbuying_centre_Mins | .1353432 | .0341912 | 3.96 | 0.000 | .0683297 | .2023567 |
| Distance_barleyfarm_Mins | -.0097022 | .0041249 | -2.35 | 0.019 | -.0177868 | -.0016176 |
| _cons | 6.168795 | .2423718 | 25.45 | 0.000 | 5.693755 | 6.643836 |
| **BCTadopt** | | | | | | |
| Main_occupation_1 | .8609933 | .3023799 | 2.85 | 0.004 | .2683396 | 1.453647 |
| sex | .3981785 | .2501851 | 1.59 | 0.111 | -.0921753 | .8885324 |
| Fertilizer_per_acre | .0424906 | .0042294 | 10.05 | 0.000 | .0342012 | .05078 |
| labour_per_acre | -.0240831 | .0075159 | -3.20 | 0.001 | -.0388139 | -.0093523 |
| Age | -.0257929 | .0090996 | -2.83 | 0.005 | -.0436278 | -.007958 |
| Household_labour | .1611601 | .0490667 | 3.28 | 0.001 | .0649912 | .257329 |
| Land_Tenure_01 | -.2942084 | .1517243 | -1.94 | 0.052 | -.5915825 | .0031657 |
| landsize_own | .0578836 | .0385211 | 1.50 | 0.133 | -.0176163 | .1333835 |
| Distance_barleyfarm_Mins | .0105921 | .0125298 | 0.85 | 0.398 | -.0139659 | .03515 |
| Seeds_per_acre | .0148324 | .004896 | 3.03 | 0.002 | .0052364 | .0244284 |
| barley_expereince_01 | .0983342 | .0240649 | 4.09 | 0.000 | .051168 | .1455005 |
| Schooling_Year | .0398626 | .0208059 | 1.92 | 0.055 | -.0009162 | .0806415 |
| ln_NBLbuying_centre_Mins | -.3945094 | .0860452 | -4.58 | 0.000 | -.5631548 | -.2258639 |
| receive_BCTtraining_02 | .5195475 | .1850515 | 2.81 | 0.005 | .1568532 | .8822418 |
| belong_group_01 | .6958353 | .1502579 | 4.63 | 0.000 | .4013352 | .9903354 |
| _cons | -2.528206 | .7349747 | -3.44 | 0.001 | -3.968729 | -1.087682 |

| | | | | | | |
|---|---|---|---|---|---|---|
| /lns1 | -1.11182 | .0605039 | -18.38 | 0.000 | -1.230405 | -.9932345 |
| /lns2 | -1.000295 | .051818 | -19.30 | 0.000 | -1.101856 | -.8987332 |
| /r1 | -.9763003 | .2609585 | -3.74 | 0.000 | -1.487769 | -.4648311 |
| /r2 | -.3629863 | .2025444 | -1.79 | 0.073 | -.759966 | .0339935 |
| sigma_1 | .3289597 | .0199033 | | | .2921741 | .3703768 |
| sigma_2 | .3677711 | .0190572 | | | .3322538 | .407085 |
| rho_1 | -.7514599 | .1135973 | | | -.9029135 | -.4340135 |
| rho_2 | -.3478417 | .1780378 | | | -.641057 | .0339804 |

```
LR test of indep. eqns. :          chi2(1) =     6.96   Prob > chi2 = 0.0083
.
```

# Appendix E: Estimation results of ESR model for gross margin function

```
. movestay ln_Gross_margin Age sex  barleyfarmsize_01  Main_occupation_1 belong_group_01 receive_extension Netwo
> rk_Connection_02 credit_need ln_total_nonbarley_income_annual , select(BCTadopt= receive_BCTtraining_02 NBLbuy
> ing_centre_Mins) nolog
```

```
Fitting initial values .....
Endogenous switching regression model            Number of obs    =        491
                                                 Wald chi2(9)     =     238.87
Log likelihood = -537.57622                      Prob > chi2      =     0.0000
```

| | Coefficient | Std. err. | z | P>\|z\| | [95% conf. | interval] |
|---|---|---|---|---|---|---|
| **ln_Gross_margin_1** | | | | | | |
| Age | .0001008 | .0018231 | 0.06 | 0.956 | -.0034724 | .0036739 |
| sex | -.109831 | .0616828 | -1.78 | 0.075 | -.2307271 | .0110651 |
| barleyfarmsize_01 | .410277 | .0291735 | 14.06 | 0.000 | .3530981 | .4674559 |
| Main_occupation_1 | .1667325 | .0988142 | 1.69 | 0.092 | -.0269398 | .3604048 |
| belong_group_01 | .1119038 | .0502364 | 2.23 | 0.026 | .0134423 | .2103653 |
| receive_extension | -.0616352 | .0490486 | -1.26 | 0.209 | -.1577686 | .0344983 |
| Network_Connection_02 | .0032931 | .052837 | 0.06 | 0.950 | -.1002655 | .1068518 |
| credit_need | -.0992281 | .0473052 | -2.10 | 0.036 | -.1919445 | -.0065116 |
| ln_total_nonbarley_income_annual | -.0631801 | .0285495 | -2.21 | 0.027 | -.1191361 | -.007224 |
| _cons | 14.56861 | .4246062 | 34.31 | 0.000 | 13.73639 | 15.40082 |
| **ln_Gross_margin_0** | | | | | | |
| Age | -.0015549 | .0036775 | -0.42 | 0.672 | -.0087626 | .0056528 |
| sex | -.0412896 | .155336 | -0.27 | 0.790 | -.3457426 | .2631633 |
| barleyfarmsize_01 | .2601605 | .0475752 | 5.47 | 0.000 | .1669148 | .3534062 |
| Main_occupation_1 | -.037685 | .1582571 | -0.24 | 0.812 | -.3478632 | .2724931 |
| belong_group_01 | -.1804915 | .1021619 | -1.77 | 0.077 | -.3807251 | .0197422 |
| receive_extension | .195187 | .0971487 | 2.01 | 0.045 | .0047791 | .3855949 |
| Network_Connection_02 | -.1027103 | .1060522 | -0.97 | 0.333 | -.3105688 | .1051482 |
| credit_need | -.1874653 | .0936415 | -2.00 | 0.045 | -.3709992 | -.0039314 |
| ln_total_nonbarley_income_annual | .1202323 | .0528383 | 2.28 | 0.023 | .0166711 | .2237936 |
| _cons | 12.11544 | .7334553 | 16.52 | 0.000 | 10.6779 | 13.55299 |
| **BCTadopt** | | | | | | |
| Age | .005673 | .0058623 | 0.97 | 0.333 | -.0058169 | .017163 |
| sex | .3569854 | .2126264 | 1.68 | 0.093 | -.0597547 | .7737255 |
| barleyfarmsize_01 | .0218714 | .083858 | 0.26 | 0.794 | -.1424872 | .18623 |
| receive_extension | .0354828 | .1541703 | 0.23 | 0.818 | -.2666855 | .337651 |
| credit_need | -.7520103 | .1335539 | -5.63 | 0.000 | -1.013771 | -.4902495 |
| ln_total_nonbarley_income_annual | .1539388 | .087206 | 1.77 | 0.078 | -.0169818 | .3248593 |
| Main_occupation_1 | .6186865 | .2673179 | 2.31 | 0.021 | .094753 | 1.14262 |
| belong_group_01 | 1.036178 | .1332184 | 7.78 | 0.000 | .775075 | 1.297282 |
| Network_Connection_02 | -.0049269 | .1680431 | -0.03 | 0.977 | -.3342854 | .3244316 |
| receive_BCTtraining_02 | .9795388 | .1504494 | 6.51 | 0.000 | .6846634 | 1.274414 |
| NBLbuying_centre_Mins | -.0050019 | .0015344 | -3.26 | 0.001 | -.0080093 | -.0019945 |
| _cons | -3.664213 | 1.267133 | -2.89 | 0.004 | -6.147749 | -1.180678 |

| | | | | | | |
|---|---|---|---|---|---|---|
| /lns1 | -1.153169 | .0630628 | -18.29 | 0.000 | -1.27677 | -1.029568 |
| /lns2 | -.4715643 | .045198 | -10.43 | 0.000 | -.5601509 | -.3829778 |
| /r1 | .6301663 | .1738043 | 3.63 | 0.000 | .2895161 | .9708165 |
| /r2 | -.0370814 | .1736788 | -0.21 | 0.831 | -.3774856 | .3033227 |
| sigma_1 | .315635 | .0199048 | | | .2789369 | .3571612 |
| sigma_2 | .6240253 | .0282047 | | | .5711229 | .6818281 |
| rho_1 | .5581667 | .1196556 | | | .2816894 | .7490629 |
| rho_2 | -.0370645 | .1734402 | | | -.3605219 | .2943504 |

LR test of indep. eqns. : chi2(1) = 9.85 Prob > chi2 = 0.0017

.

**Appendix F: Egerton University ethical clearance**

EGERTON UNIVERSITY

TEL: (051) 2217808
FAX: 051-2217942

P. O. BOX 536
EGERTON

**EGERTON UNIVERSITY INSTITUTIONAL SCIENTIFIC AND ETHICS REVIEW COMMITTEE**

**EU/RE/DIR/009**
***Approval No. EUISERC/APP/355/2024***

*22nd July* **2024**

Racheal Ninsiima
P O Box 1, Kyambogo
Telephone: +256700288028
Email: rachealninsiima@gmail.com +254798900144

Dear Racheal,
**RE: ETHICAL APPROVAL: EFFECT OF BLOCKCHAIN TECHNOLOGY ON PERFORMANCE OF BARLEY FARMERS IN EASTERN UGANDA**

This is to inform you that the ***Egerton University Institutional Scientific and Ethics Review Committee*** has reviewed and approved your above research proposal. Your application approval number is ***EUISERC/APP/355/2024.*** The approval period is ***22nd July 2024 – 23rd July 2025***

This approval is subject to compliance with the following requirements;

i. Only approved documents including (informed consents, study instruments, MTA) will be used.

ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by ***Egerton University Institutional Scientific and Ethics Review Committee***.

iii. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to ***Egerton University Institutional Scientific and Ethics Review Committee*** within 72 hours of notification

iv. Any changes, anticipated or otherwise that may increase the risks or affect safety or welfare of study participants and others or affect the integrity of the research must be reported to ***Egerton University Institutional Scientific and Ethics Review Committee*** within 72 hours.

v. Clearance for Material Transfer of biological specimens must be obtained from relevant institutions.

vi. Submission of a request for renewal of approval at least 60 days prior to expiry of the approval period. Attach a comprehensive progress report to support the renewal.

***"Transforming Lives through Quality Education"***

vii. Submission of an executive summary report within 90 days upon completion of the study to ***Egerton University Institutional Scientific and Ethics Review Committee***.

Prior to commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology and Innovation (NACOSTI) https://oris.nacosti.go.ke and also obtain other clearances needed.

EGERTON UNIVERSITY
Date. 22/07/2024
RESEARCH ETHICS

Yours sincerely.

Prof. Kennedy N. Ondimu PhD
**CHAIRMAN, EGERTON UNIVERSITY INSTITUTIONAL SCIENTIFIC AND ETHICS REVIEW CTTEE**
*KNO/BK/*

## Appendix G: Ethics clearance from Uganda Christian University

**UGANDA CHRISTIAN UNIVERSITY**
A Centre of Excellence in the Heart of Africa

Office of the Vice Chancellor
Research Ethics Committee UG-026

**NINSIIMA RACHEAL**
**Egerton University**
**+256-761413003**
**Email: rachealninsiima@gmail.com**

**UG-REC-026 APPROVAL NOTICE**

**To: Ninsiima Racheal,** Principal Investigator

**Re: UCU-REC Application titled:** *Effect of Block chain Technology on the Performance of Barley Farmers in Eastern Uganda.*

**Application Number: UCUREC-2024-1000**

UGANDA CHRISTIAN UNIVERSITY
APPROVED
UNTIL
14 JAN 2026
RESEARCH ETHICS COMMITTEE

**Version: 4.1**

**Type:** [ ] **INITIAL REVIEW**
[ ] Protocol Amendment
[ ] Letter of Amendment (LOA)
[ ] Continuing Review
[ ] Material Transfer Agreement
[ ] Other, Specify:

---

I am pleased to inform you that the **UG-REC-026;** UCUREC approved the above referenced application.

Approval of the research is for the period from **14th January, 2025, to14th January 2026**
**This research is considered minimal risk category.**
As Principal Investigator of the research, you are responsible for fulfilling the following requirements of approval:

1. All co-investigators must be kept informed of the status of the research.
2. Changes, amendments, and additions to the protocol or the consent form must be submitted to the REC for re-review and approval prior to the activation of the changes. The REC application number assigned to the research should be cited in any correspondence.
3. Reports of unanticipated problems involving risks to participants or other must be submitted to the REC. New information that becomes available which could change the risk: benefit ratio must be submitted promptly for REC review.

Research and Ethics

P.O. Box 4, Mukono, Uganda, Plot 67-173, Bishop Tucker Road, Mukono Hill
Tel: +256 (0) 312 350 885 Fax: +256 (0) 4142 90 800 Email: rec@ucu.ac.ug Web: www.ucu.ac.ug
UCUREC is accredited by Uganda National Council for Science & Technology, FDA, and National Institutes for Health of the United States of America

4. Only approved consent forms are to be used in the enrollment of participants. All consent forms signed by subjects and/or witnesses should be retained on file. The REC may conduct audits of all study records, and consent documentation may be part of such audits.
5. Regulations require review of an approved study not less than once per 12-month period. **Therefore, a continuing review application must be submitted to the RECeight weeks prior to the above expiration date of 14th January, 2026 in order to continue the study beyond the approved period.** Failure to submit a continuing review application in a timely fashion may result in suspension or termination of the study, at which point new participants may not be enrolled and currently enrolled participants must be taken off the study.
6. The REC application number assigned to the research should be cited in any correspondence with the REC of record.
7. You are required to register the research protocol with the Uganda National Council for Science andTechnology (UNCST) for final clearance to undertake the study in Uganda.

The following is the list of all documents approved in this application by **UG-REC _026:**

| | Document Title | Language | Version | Version Date |
|---|---|---|---|---|
| 1. | Protocol | English | 2.0 | 2024-12-19 |
| 2. | Focused Group Discussion Guide | English | 2.0 | 2024-12-19 |
| 3. | Informed Consent -Key Informant Interview | English | 2.0 | 2024-12-19 |
| 4. | Pair-wise comparison matrices | English | 2.0 | 2024-12-19 |
| 5. | Community Engagement Plan | English | 2.0 | 2024-12-19 |
| 6. | Questionnaire- Survey tool | English | 2.0 | 2024-12-19 |
| 7. | Questionnaire-Survey tool | Kupsabiny | 1.0 | 2024-12-19 |
| 8. | Informed Consent-Focus Group Discussion | English | 1.0 | 2024-12-19 |
| 9. | Risk Management Plan | English | 1.0 | 2024-12-19 |
| 10. | Informed Consent- Key Informant interviews | Kupsabiny | 1.0 | 2024-12-19 |
| 11. | Informed Consent-Focused Group Discussion | Kupsabiny | 1.0 | 2024-12-19 |
| 12. | Key Informant Guide | Kupsabiny | 1.0 | 2024-12-19 |
| 13. | Focused Group Discussion Interview Guide | Kupsabiny | 1.0 | 2024-12-19 |

Signed and Stamped

.................................
Prof. Peter Waiswa.
UCUREC Chairperson,
pwaiswa@musph.ac.ug

UGANDA CHRISTIAN UNIVERSITY
APPROVED
UNTIL
14 JAN 2026
RESEARCH ETHICS COMMITTEE

Research and Ethics

P.O. Box 4, Mukono, Uganda, Plot 67-173, Bishop Tucker Road, Mukono Hill
Tel: +256 (0) 312 350 885 Fax: +256 (0) 4142 90 800 Email: rec@ucu.ac.ug Web: www.ucu.ac.ug
UCUREC is accredited by Uganda National Council for Science & Technology, FDA, and National Institutes for Health of the United States of America

## Appendix H: Research clearance from Uganda

Uganda National Council for Science and Technology

*(Established by Act of Parliament of the Republic of Uganda)*

UNCST

**Our Ref: A536ES** **13 February 2025**

Racheal Ninsiima
Kyambogo University
**Kampala**

**Re: Research Approval: Effect of blockchain technology on the performance of barley farmers in eastern Uganda**

I am pleased to inform you that on **13/02/2025**, the Uganda National Council for Science and Technology (UNCST) approved the above referenced research project. The Approval of the research project is for the period of **13/02/2025** to **13/02/2026**.

Your research registration number with the UNCST is **A536ES**. Please, cite this number in all your future correspondences with UNCST in respect of the above research project. As the Principal Investigator of the research project, you are responsible for fulfilling the following requirements of approval:

1. Keeping all co-investigators informed of the status of the research.
2. Submitting all changes, amendments, and addenda to the research protocol or the consent form (where applicable) to the designated Research Ethics Committee (REC) or Lead Agency for re-review and approval **prior** to the activation of the changes. UNCST must be notified of the approved changes within five working days.
3. For clinical trials, all serious adverse events must be reported promptly to the designated local REC for review with copies to the National Drug Authority and a notification to the UNCST.
4. Unanticipated problems involving risks to research participants or other must be reported promptly to the UNCST. New information that becomes available which could change the risk/benefit ratio must be submitted promptly for UNCST notification after review by the REC.
5. Only approved study procedures are to be implemented. The UNCST may conduct impromptu audits of all study records.
6. An annual progress report and approval letter of continuation from the REC must be submitted electronically to UNCST. Failure to do so may result in termination of the research project.

Please note that this approval includes all study related tools submitted as part of the application as shown below:

| No. | Document Title | Language | Version Number | Version Date |
|---|---|---|---|---|
| 1 | Survey quesstionnaire | English | PDF | 26 November 2024 |
| 2 | Consent form | English | WORD DOCUMENT | 26 November 2024 |
| 3 | Project Proposal | English | PDF DOCUMENT | |
| 4 | Approval Letter | English | | |
| 5 | Administrative Clearance | English | | |
| 5 | Consent form for FGD_Kupsabiny | Kupsabiny | PDF | 14 January 2025 |
| 6 | FGD_English | English | PDF | 14 January 2025 |
| 7 | FGD_Kupsabiny | Kupsabiny | PDF | 14 January 2025 |
| 8 | Consent form for FGD_English | English | PDF | 14 January 2025 |
| 9 | Consent form for KII_English | English | PDF | 14 January 2025 |
| 10 | Consent form for KII_Kupsabiny | Kupsabiny | PDF | 14 January 2025 |
| 11 | KII guide_English | English | PDF | 14 January 2025 |
| 12 | KII guide_Kupsabiny | Kupsabiny | PDF | 14 December 0025 |
| 13 | Questionnaire_English | English | PDF | 14 January 2025 |
| 14 | Questionnaire_Kupsabiny | English | PDF | 14 January 2025 |
| 15 | Community engagement plan | English | PDF | 14 January 2025 |
| 16 | Risk Management Plan | English | PDF | 14 January 2025 |

Yours sincerely,

Hellen Opolot
For: Executive Secretary
**UNCST**
**UGANDA NATIONAL COUNCIL FOR SCIENCE AND TECHNOLOGY**

*LOCATION/CORRESPONDENCE*

*Plot 6 Kimera Road, Ntinda*
*P.O. Box 6884*
*KAMPALA, UGANDA*

*COMMUNICATION*

TEL: (256) 414 705500
FAX: (256) 414-234579
EMAIL: info@uncst.go.ug
WEBSITE: http://www.uncst.go.ug

## Appendix I: Publications related to the study

frontiers | Frontiers in Sustainable Food Systems

TYPE Original Research
PUBLISHED 19 March 2025
DOI 10.3389/fsufs.2025.1552637

Check for updates

OPEN ACCESS

EDITED BY
Yari Vecchio,
University of Bologna, Italy

REVIEWED BY
Francesco Bozzo,
University of Bari Aldo Moro, Italy
Ying Zhang,
University of Surrey, United Kingdom

*CORRESPONDENCE
Racheal Ninsiima
nracheal@kyu.ac.ug

RECEIVED 28 December 2024
ACCEPTED 24 February 2025
PUBLISHED 19 March 2025

CITATION
Ninsiima R, Mshenga P and Okello D (2025) Determinants of smallholder barley farmers' intentions to adopt blockchain technology: a Technology Acceptance Model approach in Uganda. *Front. Sustain. Food Syst.* 9:1552637. doi: 10.3389/fsufs.2025.1552637



# Determinants of smallholder barley farmers' intentions to adopt blockchain technology: a Technology Acceptance Model approach in Uganda

Racheal Ninsiima[1,2]*, Patience Mshenga[2] and Dickson Okello[2]

[1]Department of Agricultural Education and Agriculture Economics, Kyambogo University, Kampala, Uganda, [2]Department of Agricultural Economics and Agribusiness Management, Egerton University, Njoro, Kenya

**Introduction:** Technological change is a mega trend that drives sustainable development in the agrifood sector globally. The introduction of BanQu, a blockchain-enabled platform, aimed to address challenges like lack of transparency, side-selling, and unfair pricing in Uganda's barley value chain, but its acceptance has been slow. While blockchain adoption has thrived in developed countries and large supply chains, empirical evidence on its uptake among smallholder farmers in Sub-Saharan Africa, especially Uganda, remains limited. This study investigates determinants of smallholder barley farmers' intentions to accept blockchain technology (BCT) in Uganda.

**Methods:** The study utilized the second extension of the Technology Acceptance Model (TAM2), customized to fit Uganda's context. Quantitative data were gathered from 245 farmers in Bukwo and Kween, the two leading barley-producing districts in eastern Uganda. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM).

**Results and discussion:** The study showed that perceived usefulness (PU) significantly influenced behavioral intention (BI) and shaped perceived ease of use (PEU). Subjective norms (SUN) and voluntariness (BV) enhanced PU, while perceived behavioral control (PBC) improved PEU. Notably, BCT relevance (BR) directly influenced BI, bypassing PU. These findings provide fresh insights into rural technology adoption, highlighting PU's influence on PEU and BV's role in shaping PU. The study recommends emphasizing BCT benefits such as reducing transaction costs, leveraging social networks, and addressing resource gaps to boost acceptance. This study advances understanding of BCT adoption among smallholder farmers in emerging economies like Uganda.

KEYWORDS

**BanQu blockchain, barley value chain, intentions to adopt, smallholder farmers, Technology Acceptance Model, Uganda**

**Appendix J: Publications related to the study**

**Discover** Agriculture

Research

# Influence of social norms on blockchain technology adoption: a structural equation modelling approach among smallholder barley farmers in Uganda

Racheal Ninsiima[1,2] · Patience Mshenga[2] · Dickson Okello[2]

Received: 18 December 2024 / Accepted: 2 June 2025
Published online: 14 June 2025


**Abstract**

Innovative agricultural technologies such as blockchain (BCT) offer transformative potential for improving crop value chains, yet their adoption remains low. While prior research has focused on infrastructure, technological, and economic barriers to adoption, social factors, critical in early adoption phases within cohesive rural communities, are often overlooked. Social norms influence technology adoption by shaping individuals' perceptions of what is acceptable or expected behaviour within their community, often driving conformity to collective attitudes and practices. This study employs a social norm analysis (SNA) approach to examine how social norms influence BCT initial adoption intentions among barley smallholder farmers in eastern Uganda. Data were collected from 245 farmers using semi-structured questionnaires and analyzed with Smart PLS through structural equation modelling. The findings reveal that social norm [subjective norms (B = 0.185, p = 0.005), injunctive norms (B = 0.166, p = 0.003), normative reference groups (B = 0.125, p = 0.021), and behavioural sanctions (B = 0.390, p = 0.000)] positively shaped farmers' attitudes (B = 0.652, p = 0.002), enhancing their intentions to adopt BCT. The study recommends that stakeholders, including the government and extension officers from barley buying companies, leverage social norms alongside non-normative factors to drive BCT adoption in rural crop value chains. These insights enrich the understanding of sociocultural dynamics influencing the initial adoption of complex technologies like blockchain.

**Keywords** Blockchain technology · Social norms · Rural communities · Barley value chain · Behavioural intentions ·