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Influence of social norms on blockchain technology adoption: a structural equation modelling approach among smallholder barley farmers in Uganda

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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 · Smallholder farmers · Eastern Uganda

1 Introduction

Blockchain technology (BCT) has garnered significant global attention for its potential to enhance transparency, trust, and efficiency in agricultural value chains [1]. In developing countries, like Uganda, where inefficiencies, mistrust, and information asymmetries often plague traditional agricultural systems, BCT offers a promising solution to empower smallholder farmers

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by ensuring secure transactions and fairer market access [2]. Despite its potential, the adoption of BCT among smallholder farmers remains limited, with many contextual and behavioural factors influencing their perceptions toward embracing this innovation [3].

One critical, yet understudied factor in technology adoption is the role of social norms. Social norms, defined as the shared beliefs about acceptable behaviours within a community, often dictate how innovations are perceived and adopted within cohesive rural communities [4]. Previous studies on technology adoption, guided by frameworks such as the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT), have established the importance of external influences like perceived utility or technical features [5, 6]. However, few studies have explored how deeply ingrained social norms influence the adoption of complex technologies like blockchain, particularly in rural agricultural settings.

This paper addresses this gap by examining the influence of social norms on BCT adoption among smallholder barley farmers in eastern Uganda's Sebei sub-region. Barley farming in Uganda represents a critical value chain where trust and loyalty between farmers and buyers are essential but often undermined by practices like side-selling and contract breaches [7]. By employing Structural Equation Modelling (SEM), this paper evaluates the interplay between social norms, attitudes, and behavioural intentions to adopt BCT. Understanding these dynamics is crucial for policymakers and stakeholders to develop interventions that resonate with the cultural and social context of rural communities. Specifically, the study seeks to: (1) assess the influence of social norms on farmers' attitudes; (2) evaluate the impact of social norms on the behavioural intentions to adopt BCT; and (3) offer empirically grounded, practical recommendations to support broader BCT adoption in Uganda and similar contexts.

Social norms, encompassing both injunctive (what people approve of) and descriptive (what people typically do), social sanctions (approval or disapproval for adhering to or violating societal expectations) exert significant influence over individual and group behaviour [8]. These norms can act as both facilitators and barriers, as they reflect collective expectations and deeply embedded social practices that shape individual choices regarding new technologies, like blockchain [9]. For instance, the fear of social sanctions and the desire for social approval are key motivators that shape farmers' intentions to adopt BCT [10]. In the context of Ugandan smallholder barley farmers, social norms may dictate preferences for traditional methods, trust in technological solutions like BCT, or collective decision-making in agricultural practices.

Prior research has emphasized the significant role of social influences in shaping technology adoption within smallholder farming systems, where collective values and peer dynamics strongly impact behavioural intentions [11, 12]. However, much of this research has focused on the later stages of technology adoption [13], or on evaluating the impacts of agricultural innovations [14]. These studies often overlook the critical initial adoption phase, which plays a decisive role in determining the success or failure of adoption efforts. Furthermore, there is a notable gap in tailored studies examining the intentions to adopt BCT within Uganda's barley value chain, a crucial yet underexplored area of agricultural development.

The barley value chain, a vital livelihood source for smallholders [15], and a key input for the brewing industry [16], faces significant challenges, including price opacity, delayed payments, and side-selling. Blockchain technology offers promising solutions to these issues through smart contracts, real-time payment systems, and secure, immutable recordkeeping [17]. Moreover, blockchain has proven its potential to tackle problems like information asymmetry, side-selling, and inefficiencies in agricultural value chains, as demonstrated by successful pilot projects across Africa [2, 18]. Yet, BCT adoption among barley smallholders remains low due to infrastructural, economic, and most notably, contextual barriers rooted in social norms.

By focusing on barley farmers, a crucial segment of Uganda's agricultural economy, this paper contributes to the growing body of literature on technology adoption by integrating social norms into the analysis of BCT uptake in agriculture. It provides evidence-based insights into how community-driven behavioural expectations can either facilitate or hinder the diffusion of blockchain, offering practical recommendations to enhance adoption in similar contexts globally. Further, the study contributes to informing policymakers and technology developers on strategies to design interventions that align with local social contexts. Incorporating insights from social norms analysis into implementation strategies could accelerate the adoption of BCT, enhancing farmers' livelihoods and the overall agricultural value chain.

2 Literature review and hypotheses development

This study was anchored in the social interaction theory developed by Bales [19], which explores how individuals influence and are influenced by others through social interactions. This theory, along with Mead's [20] seminal work on symbolic interactionism, emphasizes the role of communication, shared meanings, and reciprocal behaviour in shaping human relationships and social structures. Social interaction theory is based on the idea that individuals' actions and decisions are shaped by social norms, cultural contexts, and the expectations of others [21].

In the context of this study, the theory helps to highlight how social influence, peer behaviours, and societal norms affect individual barley farmers' decisions to adopt or reject BCT. Previous studies have applied social interaction theory in the context of agricultural technology adoption and beyond, demonstrating the significant impact of social factors. For example, behavioural reciprocity among Chinese farmers [22], group or peer influence among Texas farmers [23], and the strength of social ties in South Korea [24] have all shown a strong positive influence on technology acceptance.

2.1 Social norms analysis context in agricultural technology adoption

The effects of social norms in the adoption of agricultural technology, including blockchain, cannot be over-emphasized. Scholars 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 [25]. For instance, Chung [26] 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 support 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 (TPB), which suggests that people form attitudes based on perceived social expectations [27]. 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 [28]. This is particularly important in collectivist cultures or close-knit 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 [29, 30]. This study, thus, conceptualized that social norms influence farmers' attitudes which in turn influence behaviour intention to adopt blockchain technology.

Among smallholder farmers, social norms may include informal rules and principles that group members follow without legal enforcement. Examples include reciprocity in labour exchange during peak agricultural activities like planting or harvesting without monetary compensation, shared use of equipment and tools, community-based decision-making, mutual support during times of crisis, participation in local groups and cooperative activities, and respect for elders and their advice. Smallholder farmers typically seek group acceptance and aim to avoid social criticism or sanctions from others [31]. Such being the case, social norms can impose both tangible and intangible pressure, encouraging individuals to align their behaviour with the group [32]. 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 [33]. According to [10], 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, [34] used TAM effected through PLS-SEM 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 BCT, thus we hypothesize:

S_H1: Subjective norm (SUN) has a positive and significant effect on farmer attitude (FA).

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 [35]. These norms motivate individuals to adopt behaviours that align with the majority through social rewards or constraints [36]. In this study's case, it is conceptualized that when it comes to BCT's adoption, rural barley farmers may have a socially appropriate or inappropriate set of behaviours expected from them that may influence their intentions to accept BCT. 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, [37] based on the extended theory of planned behaviour to study intentions of individuals to save energy (use of energy saving technologies) found that perceived injunctive norms were significantly but negatively correlated with intention to save energy. This study hypothesizes that:

S_H2: Injunctive norm (IN) has a positive and significant effect on farmer attitude (FA).

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, 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 [38]. In the context of BCT 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 barley farmers' decisions to either accept or reject BCT [39] examined the influence of reference groups on farmers' decisions to purchase tractors in India and found a significant positive impact. Similarly, [12] 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. Drawing from these studies, the current study proposes that:

S_H3: Normative reference groups (NRG) have a positive and significant effect on farmer attitude (FA).

Behavioural sanctions refer to the rewards or punishments that individuals receive for adhering to or violating established social expectations [40]. 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 [41]. Their results further suggested that successful technology adoption requires a village rather than an individual. A related study in India [42] 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 by hypothesizing that:

S_H4: Behavioural sanctions (BS) have a positive and significant effect on farmer attitude (FA).

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 which eventually influence farmer behaviours [27]. Subjective norms, injunctive norms, normative reference groups, and behavioural sanctions all play a role in shaping barley farmers' attitudes which consequently influence whether farmers choose to adopt or reject BCT. 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 under study, where social cohesion is highly valued, and individual behaviours are closely tied to group expectations. Therefore, understanding and leveraging social norms may be crucial for shaping attitudes and promoting the successful adoption of BCT and other innovations within the barley value chain context. The proposed conceptual model for the study is presented in Fig. 1.

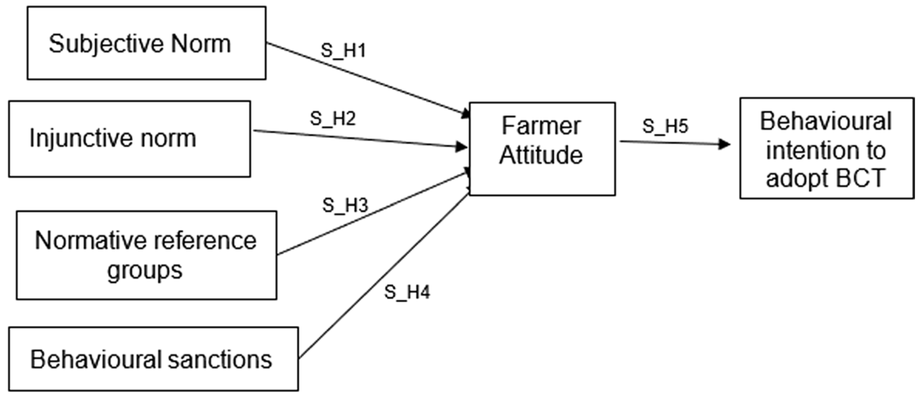

Fig. 1 Conceptual model for social norms' effect on farmer acceptance of BCT. *Source: Own elaboration*

Table 1 Identified gap in the existing literature

Existing literature	Gaps in literature	How this Study fills the gaps
Social norms have been widely examined in relation to agricultural technology adoption [43–45]	Limited focus on blockchain technology (BCT) adoption, especially among smallholder farmers	Focuses specifically on how various dimensions of social norms influence BCT adoption in smallholder barley farming
Studies from China, India, and Western countries dominate the literature on social influence in technology adoption [4, 34, 37, 39, 42]	Lack of localized empirical evidence from Uganda, especially the Sebei sub-region	Provides context-specific insights from Eastern Uganda to reflect the cultural and social dynamics of Sebei
Subjective norms are frequently explored in technology adoption frameworks like TPB and TAM [10, 46]	Less attention given to injunctive norms, descriptive norms, normative reference groups, and behavioural sanctions in BCT adoption	Expands the conceptualization of social norms by examining four different dimensions, providing a more nuanced understanding
Adoption models often focus on individual-level predictors like perceived usefulness, ease of use, or financial cost [24, 47, 48]	Underexplored social pressures and sanctions as motivating or deterring factors in blockchain uptake	Integrates social interaction theory and symbolic interactionism to explain socially driven behavioural intentions

S_H5: Farmer attitude (FA) has a positive and significant effect on behavioural intention (BI) to adopt BCT.

Based on the reviewed literature, Table 1 presents a summary of key studies and the corresponding gaps identified to justify the relevance of this study.

3 Methodology

3.1 Study area description

The study was conducted in Bukwo and Kween districts in Uganda's eastern region (Sebei sub-region) along Mount Elgon's slopes. The study focused on these districts due to their significant contributions to barley production in the country's leading barley-producing region [49]. The highland environment along the Mount Elgon slopes provides optimal conditions for barley farming, making it a suitable study site. The study areas experience two rainfall seasons, resulting in two growing periods: March–May and August–October. The economy is primarily based on crop production, though livestock rearing, including cattle, goats, sheep, and poultry, also plays a role, mainly for home consumption. Major food crops in the study area include highland rice, Sesame, sorghum, cassava, beans, and groundnuts, while key cash crops consist of wheat, coffee, and barley. Barley, the main income-generating crop, is primarily supplied to a leading brewing company, referred to as *Company B* in this study. The study area's map is shown in Fig. 2.

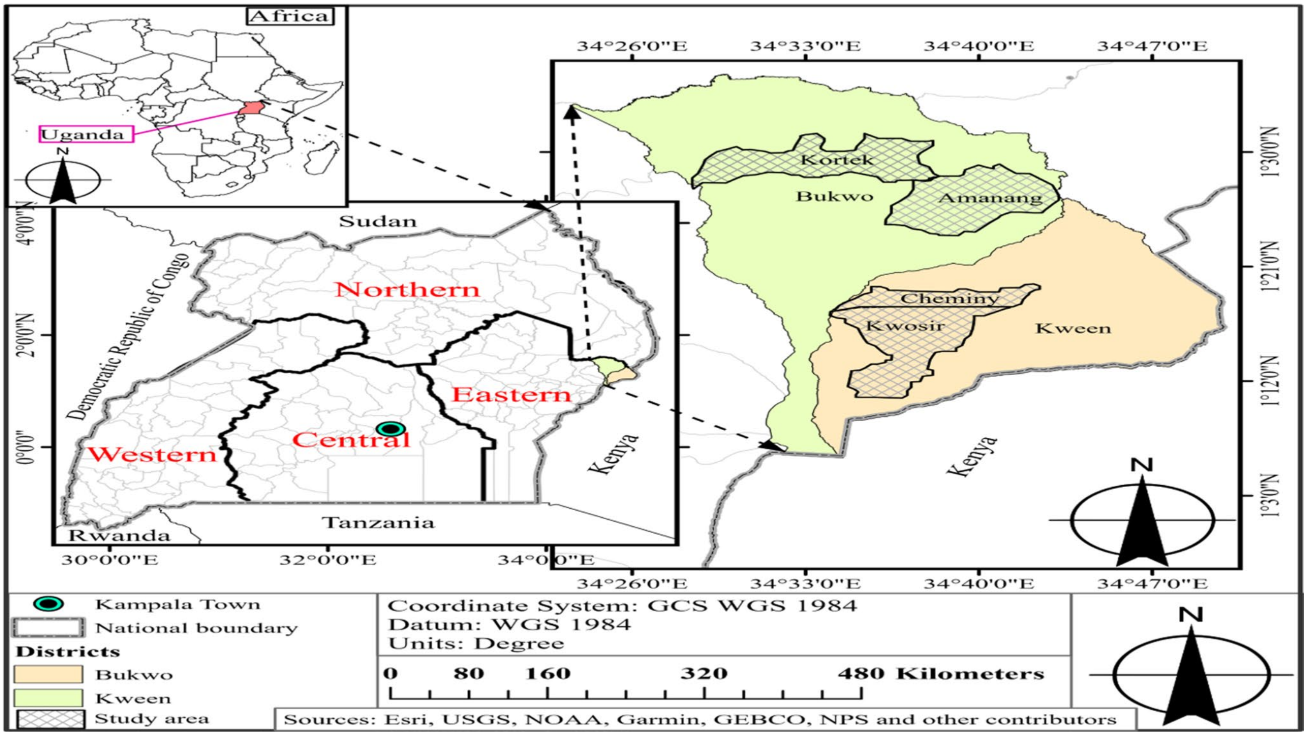

Fig. 2 Map of Uganda showing the study areas. Source: Department of Surveys and Mapping, Uganda (2024)

3.2 Research design and sampling

This study employed a quantitative, cross-sectional design, with data collected through structured questionnaires administered face-to-face by trained enumerators. A multistage sampling approach was employed, following several steps [50]. First, purposive sampling identified Bukwo and Kween, the two highest barley-producing districts in the Sebei sub-region. Next, four Sub-Counties were purposively selected based on barley production and farmer population: Cheminy and Kwosir in Kween, and Kortek and Amanang in Bukwo. From each Sub-County, two parishes were randomly selected, totaling eight: Chesimat, Kubobei, Kubulwo, and Sosho in Bukwo; and Serere, Kamwam, Kere, and Tuikat in Kween. Finally, 245 farmers were systematically selected using probability proportionate to size to account for varying parish populations.

The barley farmer population in Bukwo and Kween was estimated at 1,600, with 900 in Kween and 700 in Bukwo according to Bukwo and Kween Districts Barley Farmers' Associations. However, eligibility for the study was restricted to farmers who had interacted with BCT since its 2019 introduction, reducing the population to 800. Farmers with over 5 hectares of barley and those with less than 5 years of barley-growing experience were excluded, in line with the [51]'s definition of smallholder farmers and to enable pre- and post-BCT comparisons. This resulted in a target population of 630 farmers. Using [52]'s formula for sample size calculation

$$n = \frac{N}{1 + N(e)^2} \tag{1}$$

where N = population size (630) and e = error term (0.05), the sample size (n)was computed as n=245. Sample distribution across parishes was proportionate to population size, and systematic random sampling was applied using farmer lists provided by Company B field officers to generate systematic random numbers. The distribution of the sampled barley farmers proportionate to size is shown in Table 2.

Table 2 Distribution of the sample across the study parishes in the study areas

District	Sub-County	Parish	Percentage contribution to total sample (%)	Sample
Bukwo	Kortek	Chesimat	10	24
		Kubobei	15	38
	Amanang	Kubulwo	11	27
		Sosho	14	34
Kween	Cheminy	Serere	10	24
		Kamwam	10	25
	Kwosir	Kere	15	36
		Tuikat	15	37
Total	4	8	100	245

3.3 Data analysis

The study employed Partial Least Squares Structural Equation Modelling (PLS-SEM) to analyse the relationships among the constructs. This approach was selected due to its robustness in handling complex models with latent variables, particularly in studies involving human and social behaviour. PLS-SEM is well-suited for predictive research, accommodating non-normal data distributions [53, 54].

The model tested in this study was based on a mediated structure, where the dependent variable was Behavioural Intention to adopt BCT (BI). The explanatory variables included Subjective Norms (SUN), referring to the perceived social pressure to perform the behaviour, which behaviour in this case was to adopt or not to adopt BCT; Injunctive Norms (IN), which capture the perceived approval or disapproval of significant others; Normative Reference Groups (NRG), representing the influence of groups that individual barley farmers look to when forming behavioural decisions; and Behavioural Sanctions (BS), which reflect the expected social rewards or punishments associated with adopting or not adopting the technology. These variables were hypothesized to indirectly influence BI through the mediating variable, Attitudes towards adoption (AT), defined as an individual barley farmer's positive or negative evaluation of adopting BCT. Specifically, SUN, IN, NRG, and BS were each hypothesized to have a positive and significant effect on AT (S_H1–S_H4). In turn, AT was hypothesized to have a positive and significant effect on BI (S_H5).

All variables were operationalized using multi-item measures on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). A total of 29 items were initially developed to address both dependent and explanatory variables, and they underwent content validation through expert review at Egerton University's Faculty of Agriculture to enhance clarity, relevance, and eliminate ambiguity.

To further assess the reliability and validity of the construct items, a pilot study was conducted, and the data were analysed using Smart PLS-SEM. In line with [55]'s recommendation, items with factor loadings below 0.5 were identified; however, none were excluded at this stage, as their loadings were near the threshold, and premature elimination could have compromised the validity of the constructs. The validated questionnaire was subsequently used in the main survey. Final assessments of item-level validity and reliability, including factor loadings, composite reliability, and average variance extracted (AVE), were conducted during the measurement model evaluation phase of the PLS-SEM analysis. Although the full list of items is presented in Appendix 1, the key constructs and their roles have been summarised above to enhance clarity and ensure replicability.

4 Results and discussion

4.1 Descriptive statistics

The sampled farmers, as presented in Table 3, were largely middle-aged, averaging 43 years, with 10 years of education (equivalent to Senior Three in Uganda's education system), reflecting sufficient literacy to use BCT. On average, the sampled farmers had 9 years of experience in growing barley, and average farm sizes of 1.2 acres (0.49 hectares), aligning with the smallholder classification [51]. The sampled households were quite large, averaging 8 members, which exceeds Uganda's typical size of 5–7 members [56]. The likely reasons for larger household sizes are twofold: the need for additional income to support the family, particularly the children, which encourages engagement in barley farming

Table 3 Descriptive statistics of respondents

Variable (Continuous)		Mean	Standard deviation
Respondent's age		43	11.0
Education (years)		10	3.9
Barley experience (years)		9	3.7
Barley farm size (acres)		1.2	0.6
Household size		7.5	2.9
Variable (Categorical)	**Categories**	**Frequency**	**Percentage (%)**
Respondent's sex	Male	214	87.4
	Female	31	12.7
Marital status	Married	233	95.1
	Single	12	4.9
Primary occupation	Farming	235	95.9
	Others	10	4.1
Phone ownership status	Yes	238	97.1
	No	7	2.9
Type of phone owned	Sensory	50	20.4
	Keypad	188	76.7
Power connectivity	Grid (Hydroelectric)	3	1.2
	Solar	225	91.8
	Battery	1	0.4
	Not connected at all	16	6.5
Network stability	Stable	126	51.4
	Unstable	112	45.7

Source: Own data results

and the use of BCT; or the advantage provided by adult household members as a source of agricultural labour [57]. The majority of household heads (87.35%) were male, consistent with studies that men often have greater access to land and information, key to technology adoption [58]. Also, 95.92% of respondents were primarily farmers, highlighting the significant need for BCT in improving agricultural outcomes. Regarding technology readiness, it was reportedly high among farmers, with nearly all owning mobile phones, although the majority (76.7%) were basic keypad models. Solar power was the primary source of power for 91.84% of respondents, reflecting the limited access to national grid electricity in rural farming areas [59]. Nevertheless, connectivity challenges and network instability, affected 45.71% of respondents, posing barriers to BCT adoption.

4.2 Measurement model assessment results

This 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 Variance inflation factor (VIF), as presented in Table 4. All the factor loadings had values above the threshold level of > 0.50 recommended by [55]. The items that had loadings below the threshold level such as, SUN1, SUN5, IN5, NRG1, and NRG 2, were eliminated. Construct reliability was assessed using Cronbach's alpha (α) and composite reliability (CR), with both measures meeting the recommended range of > 0.70 [60], thereby confirming reliability. Meanwhile, the average variance extracted values (AVE) were all > 0.50, indicating that the items had high convergent validity. The collinearity measure (VIF) revealed that values of the outer model were all < 5 as recommended by [61], while common method bias (CMB) was not a problem in this study since al the VIF values of the inner model were < 3.3 [62].

Meanwhile, discriminant validity was assessed using Heterotrait-Monotrait Ratio (HTMT), Fornell-Larcker Criterion and cross loadings. From the results in Table 5, all the HTMT values were below the threshold value of < 0.90 [61], confirming that constructs were not conflated and discriminant validity was upheld. The Fornell and Larcker criterion test results confirmed that all diagonal values were greater than their corresponding vertical values, affirming discriminant validity

[63]. The cross-loading measure revealed that all the primary loadings were greater than the cross-loadings recommended by [64], confirming that no indicator was simultaneously measuring multiple constructs.

4.3 Structural (path) model analysis and hypotheses testing results

The results of the structural model analysis, conducted using PLS-SEM, are presented in Fig. 3, 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.

4.4 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 [60, 65]. In this study, the SRMR values of 0.053 for the saturated model and 0.064 for the estimated model (Table 6) fall within the acceptable range, indicating a well-fitting model.

4.5 Hypotheses testing results

Based on the results in Table 7, 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 barley farmer perceives BCT, which may then influence how they feel about the same. Farmers were encouraged to form positive attitudes regarding BCT 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 [66], 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 [67, 68], and subjective norms on perceived usefulness [69], this study provides fresh insights into the understanding of the direct influence of subjective norms on smallholder farmers' attitudes towards technology acceptance.

The Hypothesis S_H2 evaluated whether injunctive norm had a positive and significant influence on farmers' attitudes towards BCT, 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 BCT. 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 BCT was a socially expected and approved decision could have ignited positive feelings and beliefs among farmers toward BCT. Similar results were revealed by [70], that companies that take the lead in integrating BCT into supply chains influence other firms to view BCT as beneficial and a valuable factor for successful supply chain management. Also, research by [71] 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 BCT. The SNA model results supported this hypothesis at a 1% level of significance ($B = 0.125$, $t = 2.307$, $p = 0.021$). This implies that barley farmers' attitudes towards BCT were positively motivated by the behaviours (BCT 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 the use of technologies like blockchain. Barley farmers were comparing their beliefs and intentions about BCT with those of referents, and this social pressure to align with others subsequently led to more favourable attitudes toward accepting BCT. The current findings are consistent with those of [72] 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,

Table 4 Item loadings, reliability, convergent validity and collinearity tests results

Variables	Title item	Item loadings	VIF values	Reliability and convergent validity measures
Subjective norm (SUN)	SUN2	0.717	1.299	α = 0.704; CR = 0.834; AVE = 0.627
	SUN3	0.842	1.438	
	SUN 4	0.810	1.418	
Injunctive norm (IN)	IN1	0.806	1.565	α = 0.705; CR = 0.819; AVE = 0.532
	IN2	0.629	1.222	
	IN3	0.748	1.418	
	IN4	0.724	1.420	
Normative reference groups (NRG)	NRG3	0.725	1.358	α = 0.703; CR = 0.833; AVE = 0.626
	NRG4	0.846	1.540	
	NRG5	0.798	1.322	
Behavioural sanctions (BS)	BS1	0.728	1.467	α = 0.752; CR = 0.834; AVE = 0.502
	BS2	0.641	1.345	
	BS3	0.717	1.460	
	BS4	0.697	1.345	
	BS5	0.754	1.437	
Farmer attitude (FA)	FA1	0.635	1.380	α = 0.775; CR = 0.846; AVE = 0.526
	FA2	0.723	1.428	
	FA3	0.672	1.453	
	FA4	0.789	1.609	
	FA5	0.794	1.635	
Behavioural Intention (BI)	BI1	0.775	1.663	α = 0.795; CR = 0.867; AVE = 0.620
	BI2	0.727	1.411	
	BI3	0.804	1.694	
	BI4	0.840	1.826	

Source: Own data result. α denotes Cronbach's alpha, CR denotes Composite reliability, AVE denotes average variance extracted

Table 5 Discriminant validity test results

Constructs	BI	BS	FA	IN	NRG	SUN
BI	**0.787**	0.623	0.652	0.490	0.477	0.463
BS	0.797	**0.708**	0.641	0.508	0.656	0.459
FA	0.818	0.814	**0.725**	0.478	0.516	0.479
IN	0.643	0.678	0.628	**0.730**	0.349	0.381
NRG	0.632	0.888	0.672	0.491	**0.791**	0.416
SUN	0.614	0.613	0.613	0.524	0.597	**0.792**

Source: own data results. Diagonal bold values *represent square roots of AVE for each construct which are part of the Fornell and Larcker criterion values (top table), and off-diagonal values (bottom table) represent correlations between constructs*

[73] 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 BCT. The analysis results supported this hypothesis at a 1% level of significance (B = 0.390, t = 5.265, p = 0.001). One possible explanation is that barley farmers, being part of a farming community where some had already adopted BCT, may have felt pressured to do the same. Those who had not yet adopted the technology might have feared disapproval or social exclusion from their peers. This social pressure 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

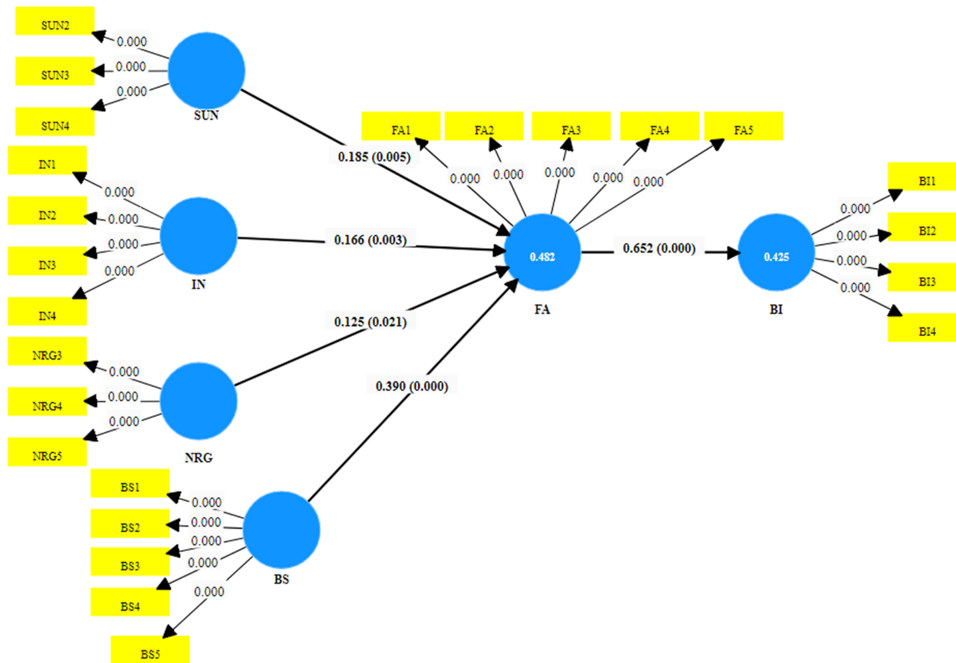

Fig. 3 Path diagram of SNA results. Source: Own data result

Table 6 Model fit analysis, explanatory power, and predictive relevance

Model fit assessment criteria	Saturated model	Estimated model
SRMR	0.053	0.064
d_ULS	4.046	4.644
d_G	1.823	1.787
Chi-square	2122.765	2134.82
NFI	0.59	0.58
Dependent variables	**R^2 values**	**Q^2 values**
BI	0.425	0.391
FA	0.482	0.444

Source: Own data result; 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

Table 7 Path coefficients in the SNA structural model

Hypothesis	Path	B	SE	T	P	Result	F^2
S_H1	SUN—> FA	0.185	0.065	2.832	0.005***	Supported	0.049
S_H2	IN—> FA	0.166	0.056	2.979	0.003***	Supported	0.038
S_H3	NRG—> FA	0.125	0.054	2.307	0.021**	Supported	0.017
S_H4	BS—> FA	0.390	0.074	5.265	0.001***	Supported	0.136
S_H5	FA—> BI	0.652	0.055	11.857	0.001***	Supported	0.740

*Source: Own data result; ***, ** denote significance levels at 1& and 5% respectively, B denotes path coefficient, SE denotes standard error, t denotes t-statistic, p denotes p-values, 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* that farmers viewed accepting BCT 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 the results of [74] where social sanctions positively influenced sheep farmers' attitudes towards farm inspections in England. In contrast to our findings, [75] reported 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 effect on barley farmers' attitudes, as investigated in S_H5, eventually had a statistically significant and positive influence on their intentions to adopt BCT. This hypothesis was supported at the 1% level of significance ($B=0.652$, $t=11.857$, $p=0.002$). The results suggest that farmers were more likely to integrate BCT into their value chain activities if they held favourable attitudes toward the technology. This finding fits within the theory of planned behaviour, which posits that positive attitudes motivate behavioural intentions [30]. The findings further align with prior research across various domains, including the agrifood sector [76, 77], business and marketing [78], and consumer behaviour studies [4], where attitudes have been shown to positively influence individuals' behavioural intentions to adopt new technologies.

4.6 Model's explanatory power and predictive relevance

The model's explanatory power was assessed by two measures namely the R^2 values and the F^2 values. R^2 measures the variance in the dependent variable explained by the independent variables in the model. The results presented in Table 6 indicate that the whole model explained 42.5% of the farmer's behavioural intentions ($R^2=0.424$) 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% [55, 79]. Similarly, the predictive relevance of the model was established from the results since all the Q^2 values were greater than the threshold of 0 [80]. The F^2 value measures the effect size or the change in the R^2 value of a dependent variable as a result of the removal of one independent variable from the model. The results in Table 7 indicate that 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 [60, 81].

4.7 Summary of key findings

This study examined how social norms influence smallholder barley farmers' attitudes and intentions to adopt blockchain-based technology (BCT) in Sebei sub-region. Structural model results showed all hypothesized paths were statistically significant, confirming the influence of social norms on technology acceptance.

Subjective norms (SUN) ($B=0.185$, $p=0.005$) positively affected attitudes, highlighting the role of peer, family, and group encouragement in fostering favourable views. Injunctive norms (IN) ($B=0.166$, $p=0.003$) also enhanced attitudes, suggesting that perceived approval from institutions like Company B legitimizes BCT adoption. Normative reference groups (NRG) ($B=0.125$, $p=0.021$), including progressive peers and extension agents, influenced attitudes through trust and observed success. Behavioural sanctions (BS) ($B=0.390$, $p=0.001$) had the strongest effect, indicating that fear of social exclusion strongly motivates adoption. Attitudes (FA) significantly predicted behavioural intention ($B=0.652$, $p=0.001$), in line with the Theory of Planned Behaviour. The model explained 48.2% of the variance in attitudes and 42.5% in intention. Overall, the findings emphasize the critical role of both supportive and coercive social norms in shaping BCT adoption and suggest that scaling efforts should harness social influence, peer learning, and respected community actors.

5 Conclusions and implications

5.1 Conclusion

The study highlights the significant role of social norms in shaping farmers' attitudes toward adopting BCT. Subjective norms, such as peer and family influences, along with injunctive norms reflecting socially approved behaviours, foster favourable attitudes, particularly when supported by trusted entities like long-term buyers or local leaders. This underscores the importance of community dynamics and collective approval in promoting innovation. Normative reference groups, including progressive farmers, agricultural advisors, and company B staff, were key in motivating adoption by acting as trusted intermediaries. Additionally, behavioural sanctions, such as the fear of exclusion, created social pressure to align with community expectations, further shaping positive attitudes. Overall, the study confirms that farmers' attitudes strongly predict their behavioural intentions, aligning with the Theory of Planned Behaviour and underscoring the need to foster positive attitudes to facilitate BCT adoption in agricultural value chains.

5.2 Theoretical implications

The study contributes to the theory of social interaction by exploring how social norms such as subjective norms, injunctive norms, reference groups, and social sanctions collectively shape farmers' attitudes and intentions toward adopting BCT. While previous technology adoption frameworks like TAM and UTAUT have studied one aspect of social norms namely subjective norms and their effect on technology usefulness or intentions [62, 63], this study's findings broaden the understanding of normative influences in technology adoption in smallholder agricultural contexts. Additionally, the findings contribute to technology adoption models by aligning with the Theory of Planned Behaviour [30], underscoring the importance of positive attitudes in driving adoption intentions and revealing how social pressures mediate these relationships. The findings further emphasize the importance of collective values and social influences within farming communities, such as Sebei, in shaping attitudes toward emerging technologies. This adds a normative perspective to theories of technology acceptance, emphasizing localized social dynamics in decision-making.

5.3 Implications for policy and practice

Policymakers and agricultural extension officers should leverage social norms to drive BCT adoption by embedding strategies within existing community structures. For instance, working through NRG (influential reference groups or trusted actors, such as progressive farmers, respected elders, and agricultural advisors), can accelerate positive attitudes toward BCT. These trusted figures should be equipped to serve as local BCT champions, facilitating peer-to-peer learning and informal endorsements that influence broader community behaviour. To further harness the power of peer influence (SUN), communication strategies should go beyond traditional awareness campaigns This includes organizing community-led demonstration projects, testimonial-based storytelling, and interactive forums where early adopters share tangible benefits and problem-solving experiences. Involvement of farmers' groups, savings groups, and cooperatives can reinforce collective learning and trust, especially when BCT is framed as a shared innovation that improves transparency and accountability.

In terms of injunctive norms (IN), highlighting visible approval and support from authoritative figures and institutions such as extension services, local leaders, and buyer companies, can signal legitimacy and reduce uncertainty. Companies implementing BCT and related technologies should invest in transparent communication strategies that explain not just how the technology woks, but how it aligns with farmers' values and benefits the entire value chain. This includes co-designing messages with farmers, providing feedback loops, and using vernacular language and local media channels to ensure accessibility.

5.4 Study limitations and areas for future research

The study was limited by geographic specificity since it was conducted in the Sebei farming community, limiting generalizability to other regions with different social or cultural dynamics. The use of a cross-sectional approach does not capture longitudinal changes in attitudes or behavioural intentions over time. The reliance on self-reported data may introduce bias, as farmers might overstate their attitudes or intentions to align with perceived social desirability. Moreover, while the study investigated multiple social norms, other potentially influential factors, such as personal norms and technological self-efficacy, were not explored.

Future research could explore how attitudes and intentions evolve, especially as farmers gain more experience with BCT. Also, expanding the study to diverse geographic locations or other agricultural value chains could provide more generalizable insights into BCT adoption. Future research could also be interested in exploring non-normative factors like trust in technology providers, perceived risk, or economic incentives, and how they interact with the normative influences would provide a more comprehensive understanding. While this study focuses on attitudes and intentions, future studies could assess how these factors translate into actual adoption behaviours.

Finally, since most household heads in the study were male, further research could investigate how demographic variables such as gender and age dynamics influence perceptions of social norms and, in turn, how these shape attitudes toward BCT adoption. In particular, exploring age and gender as potential moderators of the relationship between perceived social norms and farmer attitude could deepen the understanding of these dynamics in rural faming contexts.

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Author contributions R. N participated in conceptualization, methodology, data collection, analysis, and drafting the manuscript. P. M and D. O provided supervision, review, and editing.

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Data availability The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate The study received two ethical approvals from Egerton University's Ethical Committee (Approval No. EUISERC/APP/355/2024), and permission from the Uganda National Council of Science and Technology (Approval No. UCUREC-2024–1000) to be conducted in Kween and Bukwo Districts, Eastern Uganda, in July 2024. Before data collection, the study objectives, data confidentiality, and its importance were explained in a consent form attached to the questionnaire. Participation was voluntary, and data were collected only after obtaining participant consent.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

Appendix 1

See Table 8

Table 8 Questionnaire containing items used in SNA

Subjective norm (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 Company B staff at all levels
SUN5. I think that my use of BCT would be supported by the government of Uganda and all local authorities
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
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
Behavioural intention to adopt 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
BI3. I will recommend the use of BCT to other farmers
BI4. Given opportunity, I would produce and supply through BCT app throughout

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