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Does social capital influence the intensity of conservation agriculture adoption among smallholder farmers in Malawi?

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ABSTRACT

Addressing persistent food insecurity requires increased and sustained agricultural productivity in spite of compounding challenges of worsening climate shocks and soil degradation. However, despite numerous initiatives by stakeholders like the Malawian government, along with strong scientific evidence supporting Conservation Agriculture (CA), adoption rates in Malawi remain lower than expected. This study examined social capital as a catalyst for the adoption of CA. It used data from 1512 randomly selected smallholder farmers to investigate how different elements of social capital influenced farmers' decisions to adopt CA practices. The study findings revealed that social capital elements, namely, group membership and relationships with leadership positively influenced CA adoption. Additionally, factors such as cultivated land size, access to extension services, livestock ownership, and credit availability contributed to the number of CA practices adopted. While the transition to full CA adoption remained limited compared to partial adoption, the study revealed promising trends toward greater uptake. Consequently, these findings highlight the need for agricultural policies that promote farmer organizations, community engagement, and training programs to strengthen social networks and enhance the adoption of CA practices in Malawi.

1. Introduction

Social networking offers valuable tools for operationalizing, analyzing and quantifying connections and interactions (Borgatti Stephen et al., 1998) and how social relationships influence natural resource management and conservation practices in an agrarian economy (Groce et al., 2019; Nguyen et al., 2017). Malawi needs to sustainably increase agricultural output to feed the growing population on a per capita basis, given its high susceptibility to climate shocks and increasing land degradation. Yields of staple food crops are poor due to a lack of modern technologies and deteriorating soil fertility (Pangapanga-Phiri et al., 2024a; World Bank, 2021). Malawi continues to rank among the countries with the highest levels of food insecurity, even though it devotes more than 10% of its budget to agriculture (Matchaya et al., 2014). Low yields and land degradation in Malawi are caused by the current farming practices of the ridge and furrow systems (Bouwman et al., 2021).

Conservation Agriculture (CA) is a sustainable cropping method that can potentially reverse soil degradation, increase production, decrease labor requirements, and generate high net returns (Thierfelder et al., 2013). CA integrates interrelated principles of minimum soil disturbance (no-till), permanent soil cover, crop rotation, and intercropping. The minimal soil disturbance is no more than 25% of the soil surface for seeding, a row width limit of 15 cm (FAO, 2020; Kassam et al., 2019).

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Mulching is essential for helping soil retain moisture, as it improves water infiltration and reduces evaporation (Thierfelder et al., 2013; Thierfelder and Wall, 2012). The principles of CA are complementary and synergistic in nature. Thus, using these principles as a package not only strengthens soil health but also improves crop yield sustainability over time and increases climate resilience (Jew et al., 2020a; Tambo, 2018; Pittelkow et al., 2015; Smith et al., 2020). Additionally, combinations of CA practices generate higher crop revenue compared to adopting the practices individually (Ng'ombe et al., 2017).

African Conservation Tillage Network (ACT), and International Maize and Wheat Improvement Center (CIMMYT) also advocate the integrated approach to CA adoption, where adoption is only achieved when someone implement all the three CA packages (ACT, 2022; CIMMYT, 2015). However, farmers embracing CA do not practice all three basic principles of CA, farmers often partially adopt or dis-adopt (Pangapanga-Phiri et al., 2024a). Low implementation rates, as presented in Table 1, have been caused by divergent views about CA methods. According to Tufa et al. (2023b), the main barriers to CA adoption in Malawi include lack of interest and incentive and labor-intensive nature of CA practices. Farmers make decisions about technology adoption according to a pattern that is ingrained into a complex and highly organized system of communities, where individual choices are influenced by shared interests, group participation, and member trust (Pagliarino et al., 2020). According to Saz-Gil et al. (2021), social capital refers to the networks, norms, and trust that exist within a group and are necessary for collective action. Consequently, they help in disseminating technology information, thereby positively impacting on adoption of any agricultural innovation like CA (Corbeels et al., 2014). Farmers get knowledge about the practical applications of new technologies, including how to utilize them, what to expect, and how to handle any issues that may develop through interacting with other farmers (FAO, 2018). Adoption of agricultural technologies is dependent on social capital components as farmers engage in information exchange, resource sharing, norm-setting, and institution-building (Mapiye et al., 2023; Freeman and Qin, 2020). However, focusing on just one social capital aspect restricts the ability to explain how various elements interact to influence farmers' adoption decisions (Chetty et al., 2022; Gannon and Roberts, 2020).

Several stakeholders including governments and development partners have promoted CA to boost productivity. Studies have explored determinants of CA adoption, including the usage of CA practices (Ngwira et al., 2014a), the role of lead farmers (Pangapanga-Phiri et al., 2024a,b; Fisher et al., 2018), the CA as a solution to farmers' challenges (Jew et al., 2020), the policy integration in national agricultural rules (Chinseu et al., 2018), and the gendered perspectives on CA adoption (Khoza, 2020). Previous studies have shown mixed results regarding social capital elements in the adoption of CA. Amadu (2022) found a positive correlation between group membership and CSA adoption in a sample of 808 households in southern Malawi. Similarly, Birir (2021), from 222 households, reported that group membership increased adoption of CSA practices in Kenya.

In contrast, Olawuyi and Mushunje (2019) found a negative relationship between group membership and adoption of various CA practices. Practically, these studies have unearthed low level of adoption of CA in Malawi as shown in Table 1, ranging from 0.5% (Vuntade and Mzuza, 2022) to 60% for specific practices like intercropping (Ward et al., 2018). For instance, studies focusing on lead farmers, such as Fisher et al. (2018), report relatively higher adoption rates (56% for organic manure and crop rotation suggesting the role of networks facilitating adoption of CA. Conversely, the lower adoption rates reported in broader surveys (e.g., 2% by Tufa et al., 2023b) reflect challenges in scaling CA practices. The data also point to the uneven adoption of specific CA components. Furthermore, studies by Pangapanga-Phiri et al. (2024), Tufa et al. (2023b) and Miller (2020) focused on a single dimension of social capital, such as leadership ties, membership in farmer organizations, and kinship networks. This narrow approach limits the understanding of how social capital aspects interact and influence each other (Saukani, 2019). Ataei et al. (2024) emphasizes

Table 1
Conservation agriculture adoption rates in Malawi.

Source	Type of study	Type of CA studied	Study area	Sample size of the study	Year (s) of data collection	Adoption rates
Brendan et al., (2018)	Survey	Minimum soil disturbance	Southern Malawi	325		**3%**
Pangapanga-Phiri et al. (2024)	Survey	CA package (Minimum soil disturbance, rotation & Mulching)	Malawi, Nkhotakota	620	October to November,2016	**31%**
Tambo et al. (2018)	Survey	CA Package	Malawi; Ntchisi, Thiwi, Bwanje	3155 for all countries	Data collected in 2008	**6.09 %**
Vuntade & Mzuza (2022)	Survey	Minimum soil disturbance, Mulching &crop rotation	Southern Malawi, Nsanje	110		**0.5%**
Ward et al., (2016)	Experiment	Minimum soil disturbance, Mulching &crop rotation	Malawi; Balaka, Machinga, and Zomba	1,800	June 2014	Minimum soil disturbance; **7.6%** Mulching;**43%** intercropping;**60%**
Fisher et al., (2017)	Survey	Organic manura + crop rotation, Minimum soil disturbance, Mulching & herbicide application	Malawi; Thyolo, Chiradzulo, Machinga, Zomba, Kasungu and Lilongwe	180 lead farmers linked to by 445 followers	2016	organic manure and crop rotation:**56%**, minimum tillage: **26%,** mulching: **30%**, herbicide application: **12%**
Tufa et al. (2023a)	Survey	CA package	Malawi; Balaka, Nkhotakota, Nsanje, Chitipa, Dowa, Rumphi, and Zomba	1,512 farmers	March–June 2021	**2%**
Holden et al. (2018)	Survey	CA package	Central Malawi (Kasungu & Lilongwe) Southern (Machinga &Zomba)	175 lead farmers	2016	**2.9 %**
Jew et al. (2020)	Survey	Minimum tillage	Southern Malawi: Balaka, Machinga & Thyolo	201 farmers	August–September 2016	**≈3%**
Mango et al. (2017)	Survey	Minimum soil disturbance, Mulching & crop rotation	Southern Malawi	550 farmers		**6.7%**
Ngwira et al. (2014a)	Survey	minimum soil disturbance, mulching, and crop rotations	Malawi; Balaka, Dowa, Machinga, Nkhotakota, Salima, and Zomba	300 farmers	May–June 2010	**≈18%**

the need to explore social capital dimensions like social networks and social solidarity in the agricultural sector. To address this gap, we create an index, representing sixteen (16) social capital dimensions such as relationship with lead farmers, belonging to a farmer's groups, among others, on a larger sample size of 1,512 households.

This study contributes to the body of literature on social capital and conservation agriculture in three main ways. First, it adopts a multidimensional approach to social networking, moving beyond a singular focus on group membership to examine how various aspects of social capital facilitate the spread of information on conservation agriculture practices. Second, it explores how successful demonstrations of social capital influence farmers' likelihood of adopting different conservation agriculture practices. Third, it illustrates how social capital strengthens farmer organizations and cooperatives, enhancing collective bargaining power for inputs, access to financial resources, and group-based demonstrations of conservation agriculture. By fostering trust and collaboration, social capital ultimately reduces the perceived risks associated with adopting conservation agriculture.

2. Materials and methods

2.1. Data

We use secondary data collected by the International Institute of Tropical Agriculture (IITA) and International Maize and Wheat Improvement Centre (CIMMYT) under Adoption of Conservation Agriculture in Southern Africa (ACASA) project in 2021. To identify survey districts, EPAs, villages, and households, a multistage sampling technique was used. Seven districts were chosen based on previous and current Conservation Agricultural interventions, including three from the low agro-ecology (Balaka, Nkhotakota, and Nsanje) and four from the mid-elevation (Chitipa, Dowa, Rumphi, and Zomba) as shown in Fig. 1. Based on the frequency of CA practice, three EPAs per district and three sections per EPA were purposefully chosen. A total of 1512 households were selected randomly from 189 sample villages, 63 sections, and 21 sample EPAs.

2.2. Data analysis

We analyzed the data using descriptive statistics and econometric models. To quantify the components of social capital, we employed principal component analysis. The Negative Binomial Regression model was used to determine the influence of social capital components on adoption of CA practices and Seemingly Unrelated Regression to the analysis of determinants of social capital components. The expected sign and justification of variables are shown in Table 4.

2.3. Principal component analysis (PCA)

We hypothesized that a group of social factors influence farmers' decision to adopt conservation agriculture. Hence, the study follows Nahapiet and Ghoshal (1998) framework, where social capital is divided into three dimensions: structural, relational, and cognitive. The structural dimension shows who is connected to whom, revealing the network's structure, while the relational dimension focuses on the quality of these connections, including trust and mutual support. Finally, the cognitive dimension highlights shared values and beliefs that make collaboration easier. The study variables (Table 2) align with these categories. Relationships with leaders, reliance on networks, and group membership capture the structural dimension of social capital. Borrowing money, receiving help, and seeking advice reflects the relational dimension, emphasizing trust and support. The cognitive dimension, tied to shared values and goals, is indirectly represented by group membership duration and leadership ties. Putnam, (1995) further highlighted the complex, multi-dimensional nature of social capital, supporting the use of these interconnected variables. The measuring of

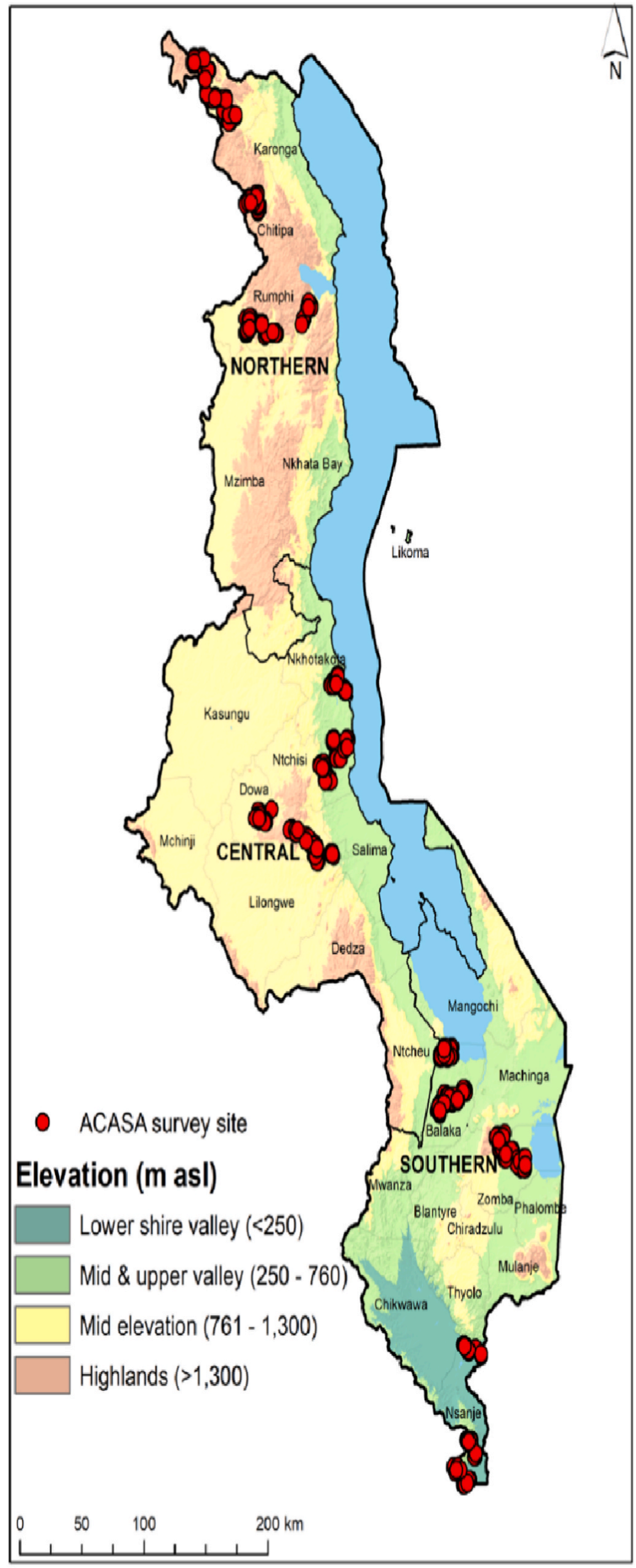

Fig. 1. Map of Malawi showing sampled district.

Table 2
Variables for the construction of social capital components.

Variables	Description
Related to Chief	1 = Yes,0 = N0
Related to Headman	1 = yes,0 = N0
Related to headwoman	1 = Yes,0 = N0
Number of years lived	Continuous
Nonrelatives within village relied on	Continuous
Nonrelatives Outside village relied on	Continuous
Relatives within village relied on	Continuous
Relatives outside village relied on	Continuous
Friendships in leadership posts	Continuous
Traders within the Village relied on	Continuous
Traders Outside the Village relied on	Continuous
Group Membership	1 = Yes, 0 = No
Group Membership Duration	Continuous
Borrow money from a network	1 = Yes,0 = N0
Material help from a network	1 = Yes,0 = N0
Seek advice for CA from the network	1 = Yes,0 = N0

social capital is difficult, and studies on social capital have drawn criticism for the use of one-dimensional measures without considering how that dimension interacts with other crucial aspects of social capital (Bhandari and Yasunobu, 2009).

Previous studies have used Principal Component Analysis (PCA) to account for the correlation of social capital elements (Belay, 2020a; Demissie et al., 2023; Ogunleye et al., 2021; Res, 2018). The current study used the PCA to quantify 16 social capital variables (Table 2). Grootaert & Bastelaer (2002) argue that social capital's intricate characteristics require analytical techniques to unpack its impact on agricultural practices. PCA serves as a robust tool in this regard, facilitating a clearer understanding of how social capital influences farmers' decisions to adopt CA practices. It is a statistical technique that is used to convert correlated variables and complex datasets by transforming the variables into a new set of uncorrelated components while retaining most of the original variability in the data (Mishra et al., 2017).

Compared to other reduction techniques like Factor Analysis or Linear Discriminant Analysis, PCA maximizes variance capture, produces uncorrelated components, and operates without assuming underlying data distributions (Greenacre et al., 2023). PCA ensures most informative aspects of the data are retained, making it highly efficient for large datasets. PCA's simplicity in computation and wide applicability across various fields further enhance its effectiveness (Jollife and Cadima, 2016; Tang et al., 2021). According to Pugno and Verme (2012), for a given j response variable, x (proxy variables, like group participation, relations to community leadership) $x_1, \ldots.., z_k$, where k < j, contains essentially the same information, so that x ϵ z. This can be expressed as in equation (1):

$$E\left(x_{ij} \middle| z_{i1}, z_{i2}, \ldots . z_{ik}\right) = \lambda_{j1} z_{i1} + \lambda_{j2} z_{i2} + \ldots + \lambda_{jk} z_{ik} \tag{1}$$

where λ is the loading on each of the k latent factors z for each individual i, constructed from j number of response variables x. The correlations are represented in equation (2):

$$\rho k, k+1 = \sum_{k=1}^{k} \lambda_k \lambda_k + 1 \tag{2}$$

The general estimating equation can be constructed as in equation (3):

$$H_i = \alpha + \sum_k \beta_k z_k, i + \sum_l \theta_l y l.i + \varepsilon_i \tag{3}$$

where z represents each of the k latent factors of social capital, and y is a set of l control variables. PCA works best when variables are correlated, but also when the distribution of variables varies. Other methods use continuous variables and a combination of binary variables and other variables that appear relevant in assessing the variable of interest (Audigier et al., 2016). To ensure each variable contributes equally to the PCA, regardless of its scale or units, data were standardized using min-max normalization to a [0,1] range. Prior to conducting PCA, data validation tests were performed, including correlation analysis and sample adequacy tests.

Six components were retained based on eigenvalues above one, which cumulatively explained more than 60% of the variation (Appendix 1). Eigenvalues measure how much variance in the data is captured by each principal component. These components were selected because they capture the most significant patterns in the data. This selection ensures that the most meaningful and influential elements of social capital are considered, while minimizing redundancy among variables. The Kaiser-Meyer-Olkin (KMO) was used to measure sample adequacy. The results showed that the sample size is adequate for the PCA analysis (KMO = 0.707) above the threshold of 0.5 (Shrestha, 2021). Furthermore, a significant result (chi-square = 3153.359; p < 0.000) from Bartlett's sphericity test was obtained, demonstrating significant correlations within the dataset and supporting the applicability of PCA (Perry and Owen, 2010). Principal component analysis on the dataset is relevant and appropriate, as demonstrated by the combined results of the KMO and Bartlett's test. A loadings analysis was performed to identify the social capital variables that show notable loading in a particular retained component (Appendix 2). A loading analysis helps identify which social capital elements contribute most to the main components or patterns that were extracted from the data.

The findings show that Component 1 loads more with non-relatives relied on within the village and Component 2 loads highly with material help from the networks. Group membership duration loads more in Component 3, while Component 4 loads more with relations to leadership. Component 5 is heavily loaded with the number of years lived in the village and relations. Varimax rotation was used to improve the components' interpretability. It is a technique that makes the primary components match the data's underlying structure. Rotation makes the components' interpretation easier by offering more significant and comprehensible patterns (Jollife and Cadima, 2016). The eigenvectors represent the directions of the principal components, while the eigenvalues indicate the amount of variation explained by each component. A general rule of thumb is to retain factors with an eigenvalue greater than one (Pugno and Verme, 2012).

2.4. Econometric framework and estimation strategy

The variables selected for this study were primarily influenced by two key factors: the availability of relevant data and the precedence set by existing literature. Specifically, these variables have been widely recognized in prior research as critical components of social capital and have been consistently linked to the adoption of CSA technologies like CA. By leveraging available data accessible and literature, the study ensures that its findings are based on established research. Table 3 shows a list of variables used in the study, how they have been operationalized, the expected sign, and justification.

Fig. 2 outlines the analytical approach used to examine the relationship between social capital and the adoption of Conservation Agriculture practices and factors affecting social capital dimension.

2.4.1. Analytical framework

2.4.1.1. Negative Binomial Regression Model (NBRM). The study draws on Everret Rodger's (1995) Diffusion of Innovations Theory, which explains how communities adopt new ideas and practices. The theory underscores the importance of social networks in driving the adoption of innovations such as CA. Therefore, the number of CA practices adopted by a farmer in this study is a function of independent variables expressed as in equation (4):

$$Y_i = f(CF, HF, FF, SCC) \tag{4}$$

Table 3
List of variables used in the study.

Variable	Unit	Sign	Justification
Age	Years	+	Older farmers have more farming expertise and likely to adopt use CA (Chichongue et al., 2020; Ntshangase et al., 2018)
Education	Years	+	Enhances the speed with which CA information is analyzed and likely lead to CA adoption (Ward et al., 2018; Tufa et al., 2023b; Tufa et al., 2023b)
Gender	1 = Female	-	Gendered labor dynamics often restrict women's ability to adopt labor-intensive agricultural practices (Silberg et al., 2020).
Marital Status	1 = Married		married people have fewer social relations with the outside as family life takes time (Belay, 2020b; Arampatzi et al., 2018)
Household size	No of family Members	+	Reflect a household's labor endowment and capacity to handle different CA tasks (Ngwira et al., 2014b)
Income	Continuous	+	People with higher incomes may have more possibility to engage in social interactions (Othieno and Shinyekwa, 2011)
Phone	1 = Yes	+	Enhances access to information and participation in social networking (Abdul-Rahaman and Abdulai, 2020)
Radio	1 = Yes	+	Radio ownership affect the quality of relationships and interaction. (Belay, 2020b; Mayasari and Chandra, 2020)
Bicycle	1 = Yes	+	Enhances access to information and networking
Motorcycle	1 = Yes	+	Improves access to information aiding mobility to extension and input service providers (Tufa et al., 2023b).
Training	Number of trainings Received	+	Training affect strength of social ties due to increased social contact and improved communication abilities (Belay, 2020b).
Distance	Distance to Network Member (km)	-	affect people's access to social networks and degree of involvement and participation (Othieno and Shinyekwa, 2011).
Frequency	Number of visits to Network member	+	Can enhance the strength of social network and trust
Cultivated land	Hectares	+	Allows farmers to spread the risk by combining use of CA with other traditional measures (Tufa et al., 2023b; Ngwira et al., 2014b)
Extension Service	Continuous	+	Extension services increase CA awareness and uptake of CA practices (Ranjan et al., 2019; Ntshangase et al., 2018)
Livestock Ownership	1 = Yes		Conflict with CA mulching uptake due to competition over crop residues for feed (Lejissa et al., 2023; Demissie et al., 2023)
Fuel source	1 = yes	-	Using crop residue as a fuel source has competing needs for CA Practices
Credit	1 = Yes	+	Access to credit can increase farmers' capacity to buy CA inputs (Workineh et al., 2020)
Agro-Ecological Zone	1 = highlands	±	Agro-ecological zones may have mixed effect on adoption of CA (Abegunde et al., 2020; Fonteyne et al., 2021; Marambanyika, 2022)
Social Capital Components	Continuous	+	Adoption of agricultural technologies dependent on social capital components (Rivera et al., 2019; Rio, 2012)
Risk aversion	1 = yes	-	Risk averse farmers are less likely to adopt CA practices (Kidane et al., 2019; Ogieriakhi and Woodward, 2022)
Subsidy	1 = yes	+	Facilitate adoption of Climate Smart Agriculture technologies (Ngoma et al., 2019)

Where Y_i is a vector of CA practices adopted by the farmers; SCC represents Social Capital Components; CF denotes Climatic factors; HF stands for Household factors; FF takes on Farm level factors. Minimum soil disturbance, mulching, crop rotation, and intercropping are denoted by *i* A decision to adopt Conservation Agriculture practices is influenced by farmers' expectation of realizing benefits compared to conventional tillage. In adopting CA practices, a farmer tries to maximize some utility functions. The utility maximizing can be with regards to adopting just one CA practice or multiple CA practices depending on farmers' preferences (Andersson and D'Souza, 2014; Liu et al., 2018). Most farmers adopt just one or two practices, and very few incorporate all three practices as a package. This makes it possible to use a count model, the Negative Binomial Regression Model (Mthethwa et al., 2022; Ojo et al., 2023). The farmer will seek to maximize the following utility function if the benefits of CA adoption outweigh conventional practices as expressed in equation (5).

$$U_{ik} = \beta x_{ik} + \varepsilon \text{ with } U_i = \sum\nolimits_{0\ otherwise}^{1\ if\ B>C}. \tag{5}$$

where U_i is the observed utility, β is a vector of parameters to be estimated, x_i is a vector of exogenous variables, and ε is the error term. Adoption is defined in terms of the number of CA practices used in the dependent variable (Aryal et al., 2018; Kassie et al., 2013; Teklewold et al., 2013). Considering that the count variable was the number of CA practices, we might have employed Poisson regression. However, Poisson regression assumes that the mean and variance of the count data are equal, which is often unrealistic in real-world data. (Ojo et al., 2023). The variance in the number of CA practices farmers adopt CA practices could be much larger than the mean due to diverse farming conditions, access to resources, and individual farmer preferences. Some farmers might only use one or two practices, while others use four or more based on their different circumstances like farm size, access to information and experience. This overdispersion can lead to inefficient and biased estimates if not properly addressed. According to Andi Bruine De Bruin et al. (2002), the negative binomial distribution model is expressed as follows in equation (6):

$$\Pr(Y = y|\lambda, \alpha) = \frac{\Gamma(y + \alpha^{-1})}{y!\Gamma(\alpha^{-1})} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \lambda}\right)^{\alpha^{-1}} \left(\frac{\lambda}{\alpha^{-1} + \lambda}\right)^{y} \tag{6}$$

The negative binomial distribution has two parameters: λ and α, where λ = the mean or expected value of the distribution, and α = the overdispersion parameter.

2.4.1.2. Seemingly Unrelated Regression (SUR). To assess socio-economic and institutional factors that influence social capital and networking among farmers, the study employed SUR. Dimensions of social capital are not straightforwardly related; they interact and support each other in complex ways. These dimensions have distinct but complementary effects on people's ability to engage in collective action (Sseguya et al., 2018). This is so because various dimensions are interconnected and affect one another rather than existing independently. There are possible causes underlying this link that cannot be tested (Chetty et al., 2022). The theoretical connection between the social

Table 4
Characteristics of adopters and non-adopters of Conservation Agriculture.

Characteristics	Description	Full Adoption (>3)	Partial adoption (2)	Non-Adoption (0)	Chi2-test
Gender	1 = Female	37.5	44.9	51.4	3.6742
		62.5	55.1	48.6	
Using Crop as fuel Source	1 = Yes	6.25	8.43	14.19	5.1945*
		93.75	91.57	85.81	
Access to Credit	1 = Yes	75	73	62	8.4929*
		25	27	38	
Agro-Ecological	1 = Highlands	25	48	42	3.9699
		75	52	58	
Risk aversion	1. Yes	6	34	46	18.4342 ***
		94	66	54	
Age	Years	49	47	45	0.4065
Education	Years	6	5.7	6	0.1323
Household size	Number of people	6	5.7	5.2	4.1129
Extension Services	Number-of extension service	3	2	1	0.8874
Cultivated Land	Hectares	4.7	3.1	2.1	14.6084***
CA tools subsidy	Number-of subsidies	1.8	1.8	1.6	4.6611*
Livestock	Tropical Livestock Units	2.8	1.7	0.9	126.3062***

*p < 0.05; **p < 0.01; and ***p < 0.001. In parenthesis, there is a number of CA practices.

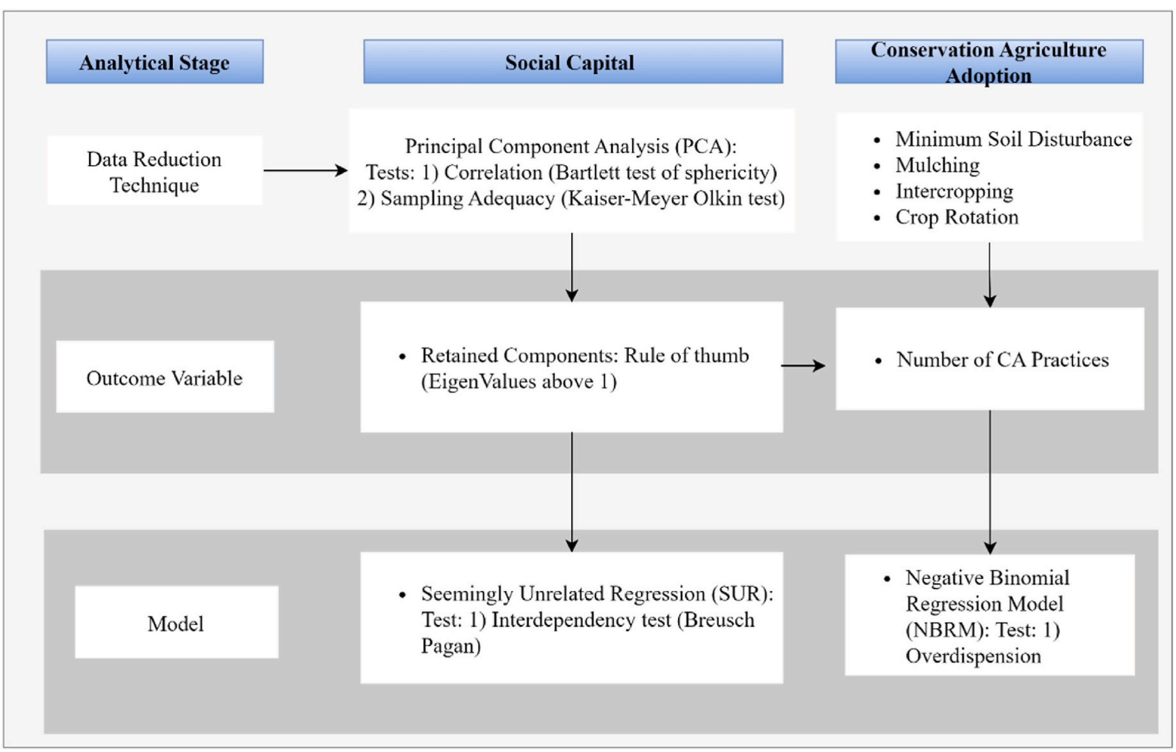

Fig. 2. Conceptual framework of analytical process.

capital dimensions through unmeasured or unobserved variables gives birth to this interdependency. This would give inefficient estimates if the equations were estimated separately via OLS. To avoid this problem, the equations are estimated as a system using SUR (Wooldridge, 2002). According to Zellner (1962), the following is the expression for the model's structural form as in equation (7):

$$y_i = X_i\beta_i + \varepsilon_i \tag{7}$$

where y_i is a (Tx1) vector of observations for the dependent variable in the *i-th* equation, X_i is a (Tx k_i) matrix of explanatory variables for *i-th* equation, β_i is a (k_i x1) vector of coefficients estimated and ε_i is (Tx1) vector of error terms. T denotes the number of observations, k_i represent number of explanatory variables in the *i-th* equation.

The SUR model accounts for the systematic correlation in the error terms (Belay, 2020b). Error structure links equations in (8); this is the difference between the values that the equations predict and the actual values. The mean sum of the errors is zero, and what unites the equations is the way they account for errors. Regarding efficiently estimating a system of multiple equations with cross-equation parameter constraints and correlated error components, the SUR model is an extension of the OLS model. The SUR assumes zero covariance between distinct equations but permits nonzero covariance between the error terms for a given individual across the equations. Compared to OLS estimates, this enables the acquisition of asymptotically more efficient estimates (Wooldridge, 2002). According to the SUR model, every equation's independent variable vector is full rank. Additionally, the model presupposes that the errors are identical, independently distributed, have a mean of zero, and have homoscedastic variance, conditional on the independent variables.

Furthermore, it is assumed that a positive definite variance matrix is required. Homoscedasticity is a key assumption of conventional linear regression. The violation of this assumption leads to heteroscedasticity. The Breusch-Pagan was considered to detect heteroscedasticity in the data (Breusch, 1979). To determine whether the error terms are associated, error correlation tests were performed prior to performing the regression. The null hypothesis of zero correlations between the equations is rejected by the Breusch-Pagan Test of Independence ($p < 0.000$). This demonstrates that SUR estimating is a suitable technique for obtaining accurate estimations.

Despite the comprehensiveness of Nahapiet and Ghoshal (1998) framework, it may not fully capture emerging dimensions of social capital, particularly those shaped by digital connectivity, which is becoming increasingly relevant. Additionally, the impact of social capital on behavior can vary across cultural, economic, and institutional contexts, potentially limiting the generalizability of this study's findings to populations with different social structures and norms. Social capital functions differently across diverse settings, as factors such as trust, community cohesion, and group dynamics are influenced by local traditions and governance structures. In regions with weaker community networks, its role in the adoption of conservation agriculture (CA) may be less pronounced. Future research could explore these contextual variations to provide broader insights into the dynamics of social capital. As social interactions increasingly shift online, future studies should consider incorporating variables that capture digital connectivity and online networking. Expanding the sample to include individuals from diverse socioeconomic and cultural backgrounds would also enhance the understanding of how social capital influences CA adoption across different contexts.

3. Results and discussion

3.1. Descriptive information

We highlight descriptive summary of key characteristics distinguishing adopters and non-adopters of Conservation Agriculture as presented Table 4. According to the results, among full adopters, only 6.25% reported using crop residues as a fuel source, while a substantial 93.75% did not. This suggests that farmers who fully adopt CA are less likely to use crop residues for fuel, which may be due to their focus on using residues for soil improvement or livestock feeding rather than for fuel. This relationship highlights the importance of managing crop residues sustainably, as it may influence the adoption of CA practices. With regards to credit access, 75% of full adopters had access to credit, compared to 73% of partial adopters and 62% of non-adopters, reflecting the crucial role of financial support in facilitating CA adoption. Risk aversion was markedly lower among full adopters, with only 6% identifying as risk-averse, compared to 34% of partial adopters and 46% of non-adopters, suggesting that risk tolerance is a significant factor in the adoption process. Regarding land size, full adopters had an average of 4.7 acres of cultivated land, while partial adopters had an average of 3.1 acres and non-adopters had 2.1 ha, indicating that land availability may influence the ability to implement CA practices. Most farmers who fully adopted CA received an average of two CA tools in subsidy and an average of three extension services. Additionally, livestock ownership was more prevalent among full adopters, with an average of 1.8 Tropical Livestock Units (TLU), compared to 1.7 TLU among partial adopters and 0.9 TLU among non-adopters, underscoring the role of livestock in supporting CA adoption, particularly through manure and crop residue utilization.

3.2. Influence of social capital dimensions on adoption of CA

Table 5 presents the effects of various factors on farmers' decisions to uptake Conservation Agriculture, focusing on the number of CA practices adopted. The practices are minimum soil disturbance, mulching, crop rotation, and intercropping. Notably, the social capital components have a role in influencing farmers' decisions to implement CA practices. The discussion will focus on the results of the Negative Binomial Regression Model.

The Poisson distribution assumes the variance equals the mean, leading to an underestimation of the standard error and inflated significance test results (Yang et al., 2007). The issue of over-dispersion in Poisson Regression Models (PRM) stems from two main assumptions. First, the Poisson process assumes that unobserved heterogeneity is not considered, as it is seen as a deterministic factor or function of the predictor variables. Second, it assumes that events in each count occur randomly and independently over time, ignoring the possibility that current events may influence future occurrences. We use the NBRM if there is over-dispersion in the Poisson distribution. The chi-square significance (Prob $\geq$ chibar2 $= 0.000$) after running an NBRM provides evidence to reject the null hypothesis that errors in the Poisson distribution do not exhibit over-dispersion. This indicates that over-dispersion is present, and we confidently proceeded with using the NBRM. Equi dispersion means that the average number of CA practices adopted by farmers would equal the variance in the count of practices adopted. In reality, this is unlikely as farmers have different levels of resources, knowledge, land sizes, and access to inputs or extension services. This leads to a wide variety in how many practices they adopt. The IRR from the NBRM was used to interpret percentage changes in the count of CA practices adopted, with IRR values above or below 1 indicating increases or decreases.

Component 3 loads highly with group membership and is statistically significant at ($p < 0.01$). Based on the p-value, we reject the null hypothesis that the social capital component does not influence farmers'

Table 5
Negative binomial regression results.

Count of CA Practices		Coefficient	IRR	Z-Statistic	P > |z|
Age (Years)		0.0008	1.0008	0.27	0.790
Education (Years)		−0.0182	0.9819	−1.48	0.138
Gender (1 = Female)		0.0143	1.0144	0.16	0.870
Marital Status (1 = Married)		0.1313	1.1404	1.27	0.203
Household size		0.0321	1.0326	1.60	0.111
Cultivated Land (ha)		0.0739	1.0767	3.07***	0.002
Extension Services		0.0808	1.0842	3.53***	0.000
Livestock (TLU)		0.0479	1.0490	2.17**	0.030
Crop Fuel Source (1 = yes)		−0.1928	0.8247	−1.41	0.157
Access to credit (1 = Yes)		0.3008	1.3510	3.21***	0.001
Agro-ecological zone (1 = Highlands)		0.1923	1.2120	2.14**	0.033
Risk Aversion (1 = Yes)		−0.1443	0.8656	−1.57	0.116
CA Tools Subsidy (1 = Yes)		0.2256	1.2531	4.02***	0.000
Comp 1		0.0271	1.0276	0.15	0.249
Comp 2		0.0338	1.0344	1.41	0.158
Comp 3		0.1100	1.1163	3.45***	0.001
Comp 4		0.0020	1.0020	0.05	0.957
Comp 5		0.1202	1.1277	2.84***	0.004
Constant		−1.9141	0.1475	−7.10***	0.000
lnalpha		−0.6314	−0.6314		
Alpha		0.5318	0.5318		
Number of observations	1,512	LR chi2 (18)	194.98	Pseudo R2	0.0666
Prob > chi2	0.000	Log likelihood	−1366.7481	Dispersion	mean
Likelihood Ratio test of alpha	0	chibar2 (01)	42.43	Prob ≥ chibar2	0.000

adoption decisions in CA. This means a unit increase in farmers group-membership increased the count of CA practices by 0.12 or 12%, holding all factors constant. Implying that farmers who are active and engaged in groups have a rate of 1.1 more points of CA practices count than counterparts who are not in groups and that it is unlikely for a farmer who is involved in group activities or with a longer membership duration to forgo the adoption of CA practices completely. Zulu-Mbata et al. (2016) and Ngwira et al. (2014a) also highlighted how group membership influences agricultural technology adoption. On the other hand, Component 5 is statistically significant at ($p < 0.01$), with a high loading of relations to chieftaincy and the number of years lived in the village. Based on the p-value, we reject the null hypothesis that social capital components do not influence farmers' adoption decisions in CA.

Specifically, the results show that holding all variables constant, a unit increase in Relation to Leadership increases the count of CA practices by 13%. This means farmers who have relations to leadership and have lived for a long period in the village are more likely to adopt CA practices over time. They might have embraced the culture of the community as a social anchorage, adopting its cultural norms and practices, including those related to agricultural technologies. Similar results were reported by Kunzekweguta et al. (2017) that social networks are significant in the uptake of CA. However, Ataei et al. (2020) note that key components of social sustainability, such as social trust, solidarity, and responsibility core elements of social capital are given minimal or no attention in the content of CA training programs. This oversight overlooks the profound impact these social factors have on the adoption and intensity of CA practices. Domingo (2023) highlights the reliance on external support, such as institutional buyers and government agencies, rather than leveraging social trust or solidarity among farmers to address challenges like middlemen control or stray animal destruction in Mung bean production. This underscores the difference in how social capital is viewed and applied in addressing agricultural challenges across different contexts.

Descriptive statistics showed that full adopters had an average of 4.7 ha of cultivated land, while partial adopters had an average of 3.1 ha and non-adopters had 2.1 ha, suggesting that land availability influences the ability to implement CA practices. This finding is further supported by statistical analysis where the size of cultivated land is significant at ($p < 0.01$); a unit increase in the size of cultivated land increases the count of CA practices adopted by 8%, holding all other variables constant. This suggests that farmers with larger cultivated land areas are more inclined towards adopting at least some CA practices. These results would mean that farmers are more willing to implement CA techniques when they have sufficient land. Tufa et al. (2023b) also reported the size of cultivated land influencing the adoption of CA practices, crop rotation in Malawi, minimum soil disturbance, and intercropping in Zimbabwe.

Interestingly, there is a significant correlation between the number of extension services a farmer receives and the count of CA practice at ($p < 0.01$). A unit increase in the number of extension services received by a farmer when all factors are constant increases the count of CA practices by 8%. Famers who fully adopted CA had received an average of three extension services. This implies that it is unlikely for farmers to forgo CA adoption if they obtain more extension services. The results are consistent with those found by Ntshangase et al. (2018), the farmers who were visited by the extension officers showed higher odds of adopting CA practices in KwaZulu Natal, South Africa. However, adoption rates are still low, possibly because of the quality of extension services, as they face limitations in funding, access to skilled personnel, and infrastructure, resulting in limited farmer outreach and support (Tata and McNamara, 2018). The findings by Ataei et al. (2024) highlight the pivotal role of social capital in addressing these challenges, particularly in private-sector extension services. They emphasize that CEOs of agricultural consultation and technical service companies should invest in social capital, as their success and survival depend on the trust and demand of farmers, underscore the broader importance of social capital in sustainable agricultural practices, where collective sharing and trust serve as critical enablers for adoption.

The results indicate a relationship between adopting CA techniques and owning livestock. Holding all factors constant, a unit increase in livestock (TLU) increases the count of CA practices by 5% at ($p < 0.01$). This means that farmers owning livestock have a rate of 1.4 more points for the count of CA practices than those farmers who do not own livestock. This is consistent with a study conducted by Chichongue et al. (2020), the number of livestock owned was found to reduce the risk associated with incorporating CA practices. Descriptive statistics further support this finding, showing that approximately 94% of farmers who fully adopted CA own livestock. The results also align with the notion that farmers rely heavily on owning animals as a source of wealth and financial resources (Myeni et al., 2019). Furthermore, a unit increase in access to credit increases the number of CA practices by 35%, holding all factors constant at ($p < 0.01$). This suggests that farmers with access to credit have a rate of 1.3 more points for the count of CA practices. This demonstrates how important financial assistance is in promoting the adoption of CA. Descriptive statistics revealed that 75% of full adopters had access to credit, compared to 73% of partial adopters and 62% of non-adopters. Credit availability helps to ease the financial obstacles that frequently prevent the adoption of sustainable farming practices. The results are consistent with the study carried out by Bhan and Behera (2014), which highlighted the importance of credit availability in enabling the attainment of inputs required for the implementation of CA. This realization supports the notion that finance acts as a bridge, helping farmers to invest in the tools and resources needed for CA (Clark et al., 2018).

According to the results, there is a noticeable pattern in the adoption of CA in highland areas. A unit increase of cultivating in the highlands increases the count of CA practices by 21%, holding all factors constant ($p < 0.01$). This shows that farmers cultivating in the highlands have a rate of 1.2 more points of CA practices count than their counterparts in the lowlands. The results point to a possible nuanced response to CA in highland locations. An earlier study by Mulimbi et al. (2019) found a similar correlation between the adoption of CA and agroecological zones. In areas like the highlands, environmental conditions like soil erosion, water scarcity, and steep terrain may present challenges to farming; social capital can play a crucial role in overcoming these obstacles. Communities with strong social networks can more effectively share knowledge, resources, and strategies to tackle environmental challenges, leading to higher rates of CA adoption. For example, farmers may come together to collectively manage land, access external support like extension services, or share labor and resources.

The number of CA tools subsidies is statistically significant at $p < 0.01$). Based on the results, a unit increase in the number of CA tool subsidies received by a farmer increased the count of CA practices by 25%. In other words, for every unit increase in the number of CA tool subsidies a farmer receives, there is a corresponding 25% increase in the number of CA practices they adopt. On average, farmers who fully adopted CA received two subsidized tools, showing how access to affordable resources directly supports their ability to adopt CA practices. This highlights how crucial subsidies are in helping farmers take up these practices. Results underscore the impact of subsidies on farmers' behavior, suggesting that even if they do not implement all recommended CA practices, the provision of subsidies for CA equipment motivates farmers to adopt at least some conservation measures. According to Piñeiro et al. (2020), subsidies play a role in encouraging farmers to integrate environmentally sustainable practices into their agricultural routines, thereby promoting the adoption of CA.

3.3. Factors affecting dimensions of social capital

The Seemingly Unrelated Regression results are shown in Table 6. We employed SUR to test the hypothesis that institutional and socio-economic factors do not affect components of social capital. The components of social capital are interconnected and exert mutual influence.

Table 6
Results' estimation of factors of dimensions of social capital based on Seemingly Unrelated Regression.

Variable	Component 1		Component 2		Component 3		Component 4		Component 5	
	Coefficient	Z	Coefficient	Z	Coefficient	Z	Coefficient	Z	Coefficient	z-value
Age	0.0271*	1.89	0.0091	0.74	0.0056	0.49	−0.0179*	−1.66	0.0081	0.83
Age Squared	−0.0002*	−1.99	−0.00008	−0.74	−0.00004	−0.43	0.0001*	1.71	−0.00006	−0.65
Education	−0.0021	−0.17	−0.00569	−0.54	−0.0094	−0.96	−0.00104	−0.11	−0.00012	−0.01
Gender (1 = Female)	−0.1466*	−1.83	0.0254	0.37	−0.1371*	−2.14	−0.0646	−1.07	−0.29140***	−5.34
Married (1 = Yes)	−0.0568	−0.56	0.0189	0.22	−0.0204	−0.25	−0.00153	−0.02	−0.01602	−0.23
Training	0.2126***	9.64	0.1123***	5.97	0.1816***	10.30	0.0993***	5.97	0.06316***	4.21
Own radio (1 = Yes)	0.0347	0.37	−0.0129	−0.16	−0.0466	−0.63	−0.0324	−0.46	−0.00592	−0.09
Own phone (1 = Yes)	−0.0511	−0.56	0.0558	0.71	−0.0245	−0.33	0.0040	0.06	0.04142	0.66
Own Bicycle (1 = yes)	0.0622	0.68	−0.1223	−1.57	0.0395	0.54	0.0626	0.91	−0.01671	−0.27
Distance to network Member (km)	0.0002	0.35	0.0009*	1.70	−0.0009	−1.63	0.00069	1.35	0.00012	0.26
Frequency of meeting network member	0.0429	2.32	0.2361***	14.96	0.0444***	3.00	0.0274**	1.96	−0.00287	−0.23
Constant	−0.8259	−2.28	−0.6950*	−2.25	−0.2788	−0.96	0.2272	0.83	−0.16916	−0.69
R-squared		0.091		0.2432		0.0956		0.049		0.0385
No of Observation					1,512					

***p < 0.01, **p < 0.05, *p < 0.1. No of Observations 1,512.
1 = Relational Social Capital, 2 = Assistance from networks social, capital, 3 = Group Membership social capital, 4 = Relation to leadership social capital, 5 = Social anchorage.

To assess whether the error terms are correlated, we conducted error correlation tests prior to performing the regression analysis. Specifically, the Breusch-Pagan Test of Independence was employed, which resulted in a rejection of the null hypothesis of no correlation between the equations ($p < 0.000$). This significant finding confirmed that SUR is an appropriate and reliable method for producing accurate estimations in our study (Breusch, 1979).

Component 1, which loads highly with non-relatives relied on within the village shows a correlation with age, age-squared, gender, and training. To begin with age, the results show a quadratic relationship of age with non-relatives relied on within the village at ($p < 0.01$). Based on the p-value, we reject the null hypothesis that social economic and institutional factors do not influence components of social capital. The negative Age Squared coefficient points to diminishing advantages of aging, which may be impacted by the middle group's focus on immediate gain. This means as the number of years of age increases, farmers increase their social networks and connections possibly because of experience, changing social roles, and evolving needs. However, once a farmer reaches a certain age, they may have established a stable network of non-relatives that meets their needs, and a further increase in age will not lead to notable changes in the number of non-relatives relied on within and outside the village. Furthermore, in old age, the number of relatives declines due to factors like physical limitations and changes in social dynamics. Elderly people exhibit a greater degree of voluntary collaboration, likely due to their life experience (Belay and Fekadu, 2021).

Gender, being female, has a negative relationship with the number of non-relatives relied on within and outside the village at ($p < 0.01$). This suggests that females may have fewer non-relatives they rely on for interaction compared to male farmers. This could be due to societal norms and cultural values, especially in the context of Malawi. At ($p < 0.01$) level of significance, results show a correlation between the number of trainings a farmer receives, and relatives rely on within the village. This suggests that farmers who receive more training rely more on non-relatives for assistance. It also indicates that training programs facilitate the development of broader social networks beyond immediate family ties.

Component 2 loads highly with material help a farmer gets from social networks. Results reveal a significant relationship between material help and training at ($p < 0.01$). This implies that farmers who attended more training have a higher chance of receiving material assistance from their social networks. Training programs not only enhance knowledge and skills but also improve farmer's ability to leverage social connections for assistance in times of need. With regards to distance, the findings show a significant positive relationship between distance to a network member and material help from the network at ($p < 0.1$). This seems counterintuitive but reflects the strength of social ties and reciprocity within social networks. Despite the physical distance, farmers within the network still maintain strong social connections and a sense of obligation to assist each other. Similar results were found by Cabrera and Najarian (2015) where social capital was found to increase with longer distances in a study to understand spatial bridging ties and social capital. In addition, material help a farmer receives from the network shows a positive correlation with the frequency of meeting a network member at ($p < 0.01$). This means a unit increase in the number of meetings increases the material help. This suggests that the more frequently farmers meet in their social networks, the more likely they are going to receive material help from the network or help each other.

Group membership loads more in Component 3, and gender shows a negative correlation at ($p < 0.01$). This implies that female farmers are less likely to join social groups within the village and may have a shorter duration of membership compared to male farmers. Societal norms and gender roles may also be the contributing factors in these scenarios. Furthermore, the results reveal a positive correlation between the number of trainings received by a farmer and group membership social capital at ($p < 0.01$). This means a unit increase in the number of trainings received by a farmer has a corresponding increase in group membership. The training programs foster strong community engagement and participation in social groups, consequently enhancing collective action. The frequency of meeting a network member shows a positive correlation with group membership at ($p < 0.01$). This means a unit increase in the frequency of interactions with network members increases group membership. Regular engagement within social networks, such as frequent meetings and interactions, contribute to strengthening the social ties and trust that are central to social capital.

In Component 4, there is a high loading of relation to leadership, which is relational social capital. Results show a negative correlation of age and a negative correlation of age-squared with relational social capital at ($p < 0.01$). Results reveal a U-shaped relationship between age and friendships in leadership positions. This suggests that both the youngest and oldest farmers can form close connections with leaders, allowing them to build friendships with those in leadership positions. These relationships may offer them greater influence and access to resources within their communities. The reason for this link is that middle-aged farmers are more focused on short-term financial benefits. As they get older, their life experiences have most likely taught them the value and importance of friendships, and as a result, they exhibit a higher degree of voluntary collaboration. These findings align with those of Belay (2020b), who demonstrated the u-shaped association between age and elements of social capital.

The number of trainings received by farmers is significantly correlated with relations in leadership positions at ($p < 0.01$). This means a unit increase in training received by a farmer increases relations to leadership social capital. The results imply that farmers who undergo more training tend to have more friendships in leadership positions within the community. Clearly, training programs do not only equip farmers with technical skills but also enhance their social capital, and in this way, farmers can contribute to the decisions of the village as they interact with the leadership. Providing training is one way to encourage a sense of solidarity among social networks, as also noted by Roy et al. (2022) and Wakefield et al. (2022). The results also reveal a positive relationship between the frequency of meeting a network member with relations to leadership social capital at ($p < 0.05$). This means a unit increase in the frequency of meeting network members increases friendship in leadership positions. This suggests that farmers who maintain regular contact within their social networks increase their visibility and connections within community leadership circles.

There is a significant negative correlation between gender and years lived in the village at ($p < 0.01$). Component 5 loads highly with years lived in the village. This means being a female farmer reduces the number of years lived in a particular village compared to male counterparts. Traditional gender roles might be a contributing factor, where males are expected to be breadwinners, perhaps household heads, leading to them establishing more permanent residence due to employment and family ties somewhat females follow the husbands moving away from their villages. Cultural expectation influences women's decision to settle in a particular area, resulting in shorter duration. In terms of training, the number of training a farmer receives has a significant positive correlation with years lived in the village at ($p < 0.01$). This means a unit increase in training received by a farmer has a corresponding increase in social anchorage. Farmers who receive more training are more likely to establish long-term residency in the village, which can contribute to their integration into the community and strengthen social ties over time.

4. Conclusions and policy Implication

This study examined the effect of social capital on the adoption of conservation agriculture (CA) among smallholder farmers in Malawi, using data from 1,512 randomly sampled smallholder farmers. The findings highlight the significant role of social capital in influencing CA adoption. Specifically, active group membership and longer residency in a village were positively associated with the number of CA practices adopted, underscoring the importance of fostering strong social networks within farming communities. To enhance the adoption of CA practices among smallholder farmers, policies should prioritize the formation and strengthening of farmer groups and cooperatives, particularly in areas where such structures are underdeveloped. Additionally, investing in training programs for these groups and promoting inter-group networking can facilitate knowledge exchange and the dissemination of best practices. Given their deep community ties and influence, long-term village residents should be leveraged as champions for CA adoption through agricultural extension services. Furthermore, considering the positive correlation between cultivated land size and CA adoption, conservation agriculture policies should provide targeted support to farmers with larger landholdings, as they are well-positioned to implement CA practices on a broader scale. To maximize outreach, agricultural extension services should expand their reach and frequency through digital technologies such as mobile phones, SMS alerts, and radio programs. Farmer Field Schools should also be promoted to encourage peer learning and practical demonstrations. Lastly, policies to improve farmers' access to credit should be strengthened to facilitate CA adoption. Stakeholders can support this by increasing the availability of tailored financial products such as low-interest loans, microcredit, or grants designed specifically to encourage investment in CA practices.

CRediT authorship contribution statement

Harry Mathanda: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Innocent Pangapanga-Phiri:** Writing – review & editing, Writing – original draft, Software, Data curation, Conceptualization. **Adane Tufa:** Writing – review & editing, Writing – original draft, Software, Methodology, Conceptualization. **Julius Mangisoni:** Writing – review & editing, Writing – original draft, Conceptualization. **Arega Alene:** Writing – review & editing, Software. **Hambulo Ngoma:** Writing – review & editing, Supervision, Data curation, Conceptualization. **Horace Happy Phiri:** Writing – review & editing, Data curation, Conceptualization. **David Chikoye:** Writing – review & editing, Data curation, Conceptualization.

Declaration of competing interest

The authors of the work that has been submitted, "Does Social Capital influence adoption of Conservation Agriculture among smallholder farmers in Malawi", hereby declare that we do not have any conflicts of interest to report. We affirm that the research presented in this paper was conducted impartially and without bias. Additionally, we confirm that the findings and conclusions presented in the manuscript are based solely on the analysis of the data and do not reflect any external influences or affiliations that could potentially compromise the integrity of the research.

Appendix 1. Rotated Principal Components

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp**1**	3.061	0.897	0.191	0.191
Comp**2**	2.164	0.650	0.135	0.327
Comp**3**	1.514	0.211	0.095	0.421
Comp**4**	1.302	0.261	0.081	0.503
Comp**5**	1.042	0.024	0.065	0.568
Comp**6**	1.017	0.081	0.064	**0.631**
Comp7	0.937	0.046	0.059	0.690
Comp8	0.891	0.104	0.056	0.746
Comp9	0.787	0.103	0.049	0.795
Comp10	0.684	0.095	0.043	0.838
Comp11	0.590	0.080	0.037	0.874
Comp12	0.510	0.038	0.032	0.906
Comp13	0.472	0.038	0.029	0.936

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Component	Eigenvalue	Difference	Proportion	Cumulative
Comp14	0.433	0.105	0.027	0.963
Comp15	0.329	0.061	0.021	0.983
Comp16	0.268	.	0.017	1.000

Number of observations: 1,512 Number of Component.

Appendix 2. Rotated component loadings from elements of social capital

Variable Components	1	2	3	4	5	6
Related to Chief	−0.0108	0.0083	−0.0376	**0.7175**	−0.0698	0.0548
Related to Headman	−0.0360	−0.0230	0.0233	0.0690	0.0122	**0.8690**
Related to headwoman	−0.0021	0.0242	0.0047	−0.0775	**0.6923**	0.0703
Number of years lived	−0.2211	−0.0919	0.0560	0.2235	**0.5036**	−0.3446
Non relatives within village relied on	**0.4948**	0.0032	0.0104	−0.0219	−0.0303	−0.0618
Non relatives Outside village relied on	**0.4666**	0.0015	0.0090	−0.0020	−0.0056	0.0311
Relatives within village relied on	0.3799	0.0399	0.0480	0.1332	0.0044	−0.1902
Relatives outside village relied on	**0.4622**	0.0333	0.0100	0.0676	−0.0998	−0.0917
Friendships in leadership posts	0.0525	0.0154	0.0225	**0.6163**	0.0801	0.0791
Traders within the Village relied on	0.2683	−0.0019	−0.0427	−0.1423	0.2997	0.2176
Traders Outside the Village relied on	0.2325	−0.0719	−0.0707	−0.0285	0.3871	0.1026
Group Membership	0.0153	−0.0369	**0.6928**	−0.0039	−0.0269	0.0255
Membership Duration	−0.0042	0.0286	**0.7102**	−0.0181	0.0349	0.0105
CA advice from the network	−0.0139	**0.5483**	0.0225	0.0038	−0.0390	0.0210
Borrow money from the Network	−0.0007	**0.5651**	−0.0044	0.0218	0.0397	−0.0529
Material- help from the network	−0.0040	**0.6001**	−0.0040	0.0054	−0.0003	−0.0245

Loadings higher than 0.40 are shown in bold.

1 = Relational Social Capital, 2 = Assistance from networks social, capital, 3 = Group Membership social capital, 4 = Relation to leadership social capital, 5 = Years lived in the village.

Data availability

Data will be made available on request.

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