Does the farmer's social information network matter? Explaining adoption behavior for disaster risk reduction measures using the theory of planned behavior

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Acknowledgments

The authors gratefully acknowledge funding from Flemish Inter-University Council (VLIR-OUS) through the TEAM project (UG2019TEA492A105): Digital citizen science for community-based resilient on environmental management (D-SiRE). Special thanks to the field research team comprised of Esther Namara, Safina Tuhaise, Hadijah Nansamba, Benedicto Akoraebirungi, and Mark Kaahwa for the tireless effort amidst the tough Covid period. Lastly, we acknowledge the effort by all the citizen scientists in the study area who worked as field guides.

Abstract

Smallholder farmers' vulnerability to climate-related disasters in Sub-Saharan Africa is increasing, partly due to land-use changes and limited information about the adoption of farm-based Disaster Risk Reduction (DRR) measures. Classical agricultural extension workers are increasingly less trusted because they tend to transfer information not targeted to DRR, and rarely reach remote areas vulnerable to disasters. By extending the Theory of Planned Behavior (TPB), this study assesses whether Social Information Networks (SIN) can shape farmers' perspectives regarding the adoption of DRR measures. Cross-sectional data were collected from 602 randomly selected households from Rwenzori and Ankole in Western Uganda, the sub-regions that are prone to landslides and floods. Results from the structural equation modeling demonstrate TPB as a strong framework to explain adoption behavior for DRR measures. Results show Perceived Behavioral Control (PBC) as a stronger driver of intentions than subjective norm and attitudes. Intentions to apply DRR measures are significantly associated with actual adoption. Farmers' adoption behavior to control landslides and floods is directly correlated since the same location might simultaneously be at risk of such interacting disasters. Furthermore, SIN significantly predicts adoption intentions directly, and indirectly through PBC, subjective norm, and attitude. PBC and professional networks being the main drivers of adoption intentions suggests that the role of extension services cannot be substituted by informal social networks but the two should be complementary. Thus, the study shows the need to build the technical capacity of extension staff and informal networks in DRR measures to train and transfer information to farmers.

Keywords: theory of planned behavior, disaster risk reduction measures, structural equation modeling, adoption intention, landslides, and floods

1. Introduction

Climate change has shaped the debates at the global level to generate ideas for adaptive land-use policy and practices (Stavi et al. 2022). The impetus is provided by the evidence: between 1970 and 2019, climate change-related disasters accounted for 91% of the global disaster events, with hydrological disasters, mainly floods and landslides accounting for 45% (Cavallo et al. 2021). While the two disasters can happen separately but they tend to occur as cascades where landslides trigger floods due to debris and dam formation (Jacobs et al. 2016), hence, the vulnerabilities tend to interact. This can be worse when the escalation points of the primary disaster (landslide) leads to secondary effects (floods) with greater impact (Alexander and Pescaroli 2019). Several deaths resulting from such disasters are reported in different countries. According to CRED and UNDRR (2021), the effect of floods and landslides has been heavily felt in Africa and Asia, since 2006, whereby about 1200 deaths were recorded and seven million people were affected by floods in Africa. In the same period, Asia's monsoon flooding associated with landslides affected 5.4 million people in Bangladesh and caused over 400 deaths in Nepal. The impact of such disasters is exacerbated by high population growth rates, estimated at 2.3% for developing countries in 2019 (compared to 0.2% in developed countries) (UN 2019), which leads to the degradation of fragile ecosystems for agriculture (Caffaro et al., 2019). Therefore, farmers are both key contributors and the most affected by the disasters (Jacobs et al., 2019).

Studies such as Maes et al. (2018) and Ma et al. (2021) suggested the need to empower farmers to lead the implementation of farm-level Disaster Risk Reduction (DRR) measures such as diversion channels and tree planting to avert shallow landslide and flash flood risks through soil reinforcement and erosion control. While diversion channels were selected to represent structural/ mechanical and hazard-specific mitigation measures, tree planting is a biological measure that can deal with multi-hazard impacts (Kumawat et al. 2020; Mubiru et al. 2018; Osuret et al. 2016). The two are the most practiced measures for soil conservation in the area (Maes et al., 2018; Mugonola, 2013). They can also be applied together to comprehensively mitigate the impact of disaster risk or further reinforced with several farm-based soil conservation innovations such as contours, terraces, ridges, grass rows, and grass stripes. However, low adoption of such measures by smallholder farmers in remote areas vulnerable to disasters is still reported (Jacobs et al., 2019).

Limited access to information is one of the challenges explaining farmers' low adoption of DRR strategies (Kabbiri et al., 2017; Shannon & Motha, 2015). A multi-hazard approach to DRR recommended by the Sendai framework[1] aims at strengthening farmers' resilience to disasters through the adoption of farm-based strategies through access to information (UNISDR, 2015). According to Rogers (2003), the adoption of an innovation depends on information targeting to increase awareness of the potential adopters which requires an effective communication channel. However, Mertens et al. (2018) argued that awareness, per se, is not sufficient to ensure the adoption of DRR

[1]**Sendai Framework** (Sendai Framework for DRR 2015-2030) is an agreement adopted at the Third United Nations World Conference on Disaster Risk Reduction in 2015 in Japan. The framework focuses on the development agenda that provides the Member States with concrete actions against the risks due to disasters (UNISDR, 2015).

strategies if farmers' self-efficacy/ Perceived Behavioral Control (PBC) is low. This suggests the need to explore the interaction between psycho-social factors and effective information transfer approaches (Jiang et al. 2018).

The Theory of Planned Behavior (TPB), which postulates that psychological constructs, mainly attitude, subjective norms, and PBC as the main determinants of actual behavior through intentions (Fishbein & Ajzen, 1975), has popularly been applied to explain adoption behavior in most studies (Yang & Wu 2021; Feng et al. 2021). Nonetheless, Al-Debei et al. (2013) pointed out the theory's limited capacity to account for the intention-behavior gap, especially in developed countries. Consequently, several studies have applied an extended TPB by including other variables beyond the three TPB constructs to increase robustness: Pérez-Macías et al. (2020) extended TPB through network ties, and shared language to explain entrepreneurship intentions, while Yang and Wu (2021) extended the TPB through social media exposure to health information to explain the protective behavior during air pollution, and both extensions improved the theory's predictive power. Whether or not the extension of the TPB through farmers' social information networks explains adoption behavior for DRR measures for landslides and floods remains unclear.

Like many other developing countries with economies largely based on agricultural production, Uganda still relies on classical extension programs to deliver information to farmers about agronomic practices (Vasilaky and Leonard 2016). Such programs have limited spatial coverage, are less proactive, expensive, and too general in terms of focus (Maes et al. 2018). As such, several studies like Mertens et al. (2018) and Wang et al. (2018) argue that classical extension is ineffective in the transfer of information related to DRR strategies to farmers in remote settings due to the complex (general) nature of training content and limited access to such areas through poor roads. According to Vasilaky and Leonard (2015), social networks present a cost-effective and inclusive approach to disseminating regular and timely information in remote areas. Information by locally-developed networks can play a role in improving farmers' knowledge and attitudes about farm-based DRR measures for landslides and floods. A Social network is a form of social capital consisting of individuals (actors) interacting consciously to aid the flow of resources (Abid et al. 2017). When used to transfer information, social networks can be referred to as Social Information Networks (SIN) (Murendo et al., 2018). There are two main categories of networks, i.e. professional and informal networks (Pratiwi and Suzuki 2017). These two networks can further be studied in terms of how actors are related (kinship) suggesting strong (usually informal networks) or weak networks (professional networks), if dominated by relatives or less related members, respectively (Ramirez 2013).

A study on the linkage between SIN and the adoption of DRR measures is necessary because when affected by disasters, people largely depend on relatives, neighbors, and friends for information and other survival strategies, and this might influence their land-use decisions. Also, the spatial and temporal relations between landslides and floods leading to cascades (Gill & Malamud, 2016) might influence farmers' land-use decisions. This demands a synthesis that integrates such interaction to shape effective management priorities, avoid underestimating the risk from one disaster event and reduce vulnerability to other spatially related disasters. However, there is a dearth of studies that link SIN to DRR strategies' adoption behavior from a TPB perspective in developing countries. By focusing on smallholder farmers' adoption behavior for landslides and floods, this study addresses the main question: can the farmer's SIN explain adoption intention and actual behavior for DRR strategies using the TPB perspective? The study is premised on three specific questions: (1) How one's intention to adopt DRR strategies is influenced by the TPB constructs, namely attitude, PBC, and subjective norm, and how does intention determine actual adoption? (2) Considering the temporal and spatial relations, is the farmer's intention to control landslides directly correlated to reducing floods? (3) Does the farmer's SIN influence adoption intentions directly or indirectly through attitude, PBC, and subjective norm?

To answer the research questions we apply Structural Equation Modelling to analyze cross-sectional data collected in October 2020 from 602 agricultural households in the Rwenzori and Ankole sub-regions in Western Uganda. It is an interesting case study region because it is typical of a remote area prone to landslides and floods attributed to its location on Rwenzori mountain with high relief and incised valleys upstream, sharply transitioning to flat lowland downstream (Bwambale et al. 2022). The slopes of the mountain are characterized by soft alluvial soils and high bi-model orographic rainfall (Jacobs et al. 2017; Nseka et al. 2019). The area is predominantly inhabited by smallholders farmers, whose farming activities increase the slopes' fragility. The rest of the paper is structured as follows: In section 2, we elaborate on the TPB constructs and introduce the concept of social networks. Then, we describe the empirical approach, the study area, sampling, and analytical procedure in section 3. Lastly, the results, discussion, and conclusions are discussed in sections 4 and 5, respectively.

2. Theoretical framework: Theory of planned behavior and social networks

Conceptually, actual behavior refers to an individual's actions, usually preceded by strong intentions (Jafarkarimi et al., 2016). The intention is an anticipated outcome that guides planned actions, and is indicative of how much someone is willing to invest to perform a particular behavior (Sanne and Wiese 2018). However, predicting human intention is quite complex: it is driven by extrinsic factors such as socio-demographic attributes, and intrinsic factors, mainly psychological aspects like attitude, most of which are highly unobservable (Anwar et al., 2020). The TPB, which evolved from the theory of reasoned action (Fishbein & Ajzen, 1975), was proposed to explain such behavior. TPB postulates that intention is influenced by three main psychological constructs: (1) Attitude, which is inextricably linked to personal beliefs and now's evaluation of whether a behavior is positive or not. (2) PBC (self-efficacy), which refers to one's perceived ability to engage in or have control over behavior (Maleksaeidi and Keshavarz 2019). (3) Subjective norm (social norms), which refers to perceived social pressure from others considered important such as family and friends (Borges and Oude 2016). The recent application of the TPB is criticized for merely being based on logical behavior, especially since it assumes strict rationality in decision-making (Jiang et al., 2018). Also, the theory has limited consideration of socio-economic and information-related drivers of intention (Maleksaeidi & Keshavarz, 2019).

Social networks represent an invaluable form of social capital consisting of individuals (actors) interacting consciously to aid the flow of resources in disadvantaged rural communities (Abid et al. 2017). They can be professional networks or informal networks (Pratiwi and Suzuki 2017). Furthermore, Ramirez (2013) describes the two social networks based on kinship, work relations, and affiliations, suggesting strong networks (related to informal networks) if actors are related, work together or are affiliated to a similar organization or weak ties (professional networks), if otherwise. While information from professional networks covers perspectives and issues from a wider geographical area and tends to be technical, it is usually general and may influence one's attitude less than targeted information from personal, informal, and intra-village networks (Caffaro et al. 2019). For instance, Jackering et al. (2019) revealed that during classical agricultural extension sessions, most of the information transferred focuses on general aspects of agronomy with limited focus on specifics such as marketing and nutrition. The study indicated that more sensitive, targeted information like nutrition is usually shared among family members, pointing at the role of kinship. Contrastingly, a study by Liu et al. (2017) argued that weak ties (professional networks) are key in the diffusion of novel non-redundant information due to the bridging of two otherwise unconnected network clusters.

Fishbein and Ajzen (1975) argued that, apart from attitude, subjective norm, and PBC, other factors, usually influence intentions indirectly but through these three constructs. To this end, Pérez-Macías et al. (2020)'s study revealed that network ties enhance the explanatory power of the TPB on the entrepreneurial intentions of online students, but only indirectly. Hence, the three TPB constructs could mediate the relationship between SIN and intention. Kumar (2015) defined mediation as a situation where the effect of an independent on a dependent variable is explained by a mediator variable. A TPB-mediated effect of information on intentions means that the more information is shared the higher the household's perceptions (PBC, subjective norm, and attitude) improve and the chances that such perceptions lead to a higher intention to adopt DRR strategies. Next, we explain how the TPB and SIN were operationalized in this study.

3. Materials and methods

3.1. Study area

Uganda is located in the tropical region of Africa (**Fig. 1**). Specifically, the study was carried out in the Western Uganda districts of Kasese (0.06°N, 30.06°E), Bundibugyo (0.68°N, 30.02°E), Buhweju (0.29°S, 30.29°E) and Bushenyi (0.48°S, 30.20°E). Kasese and Bundibugyo (Rwenzori sub-region) are vulnerable to landslides and floods due to their location on the slopes of the Rwenzori Mountains, Uganda's highest mountain (5109m above sea level), characterized by incised valleys upstream, sharply transitioning to flat lowland downstream (Bwambale et al. 2022; Jacobs et al. 2017; Jacobs et al. 2019 and Mertens et al. 2018). The sub-region receives a high bi-modal orographic rainfall, about 1540mm (Nseka et al., 2019), induced by the convection of moist areas of the Congo Basin (Jacobs et al., 2016). The sub-region is supplied by several rivers such as Nyamwamba, Nyamugasani, Rubilhiha, and Humya associated with regular floods. Lake George and Lake Edward are the major lakes covering the lower part of the Rwenzori mountain. Bushenyi and Buhweju districts (Ankole sub-region) are selected because of their vulnerability to landslides and floods yet they received less attention in recent studies (Nseka et al., 2019). The four districts are covered by D-SiRE[2] project (2019-2023), which played a role in the choice of the study area by mapping disaster

[2]**D-SiRE** is Digital citizen science for community-based resilient environmental management. It is a TEAM project under VLIR-OUS, in which citizen scientists known as geo-observers are recruited on recommendation by the local community, and trained in reporting disaster events

hotspots. We focus on smallholders and the uptake of DRR strategies because they are predominant on the slopes and their poor farming activities exacerbate the fragility of the vulnerable ecosystems (Mertens et al. 2018).

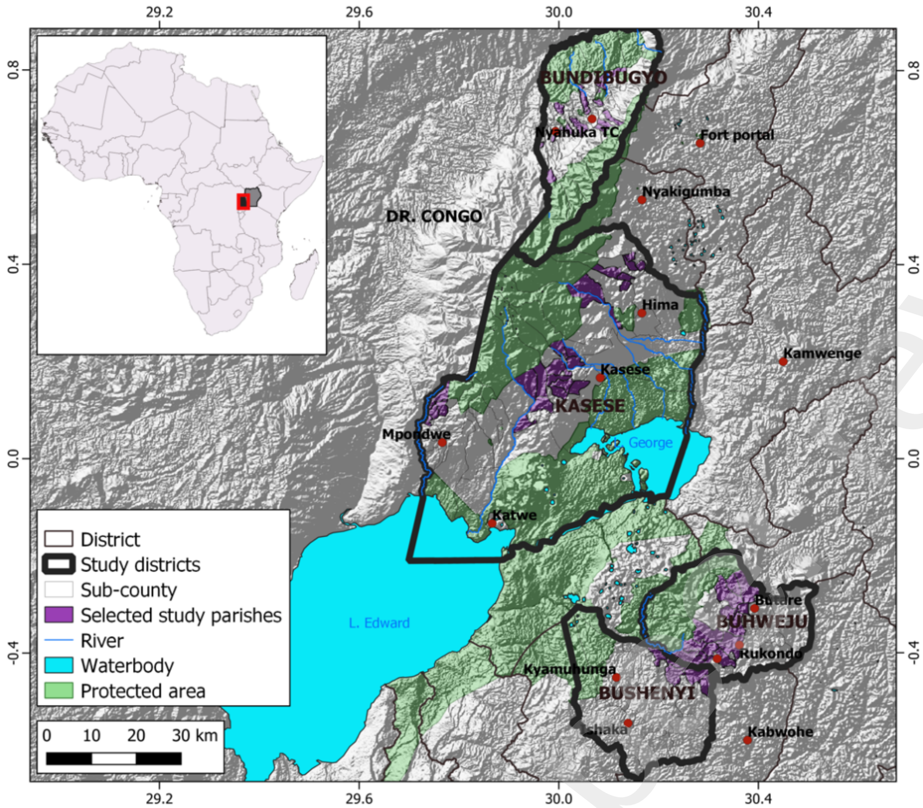

Fig. 1 Location of the study districts showing sub-counties covered

3.2. Survey procedure

Two Focus Group Discussions (FGDs) per district were conducted to obtain insights into the adoption and effectiveness of existing DRR strategies. Ten respondents participated in each FGD, including an agricultural extension worker, a parish chief, two village chairpersons, a citizen scientist, and five farmers (male and female). We followed the steps proposed by Breen (2007) for conducting FGDs including preparatory, actual, and post-session practices. A well-moderated discussion using moving debate focused on the pre-developed points, as suggested in Onwuegbuzie et al. (2009). Through observation and narratives, different landslide and flood risk reduction measures were recorded. The results from the focus groups guided the preparation of the questionnaire, which was delivered to the respondents using SurveyCTO software on android phone tablets, starting with a forty-respondent pilot survey in Bundibugyo District. The data from the pilot were not included in the final analysis but were used to clarify questions and to reduce the length of the questionnaire. The face-to-face household survey was conducted in the respective local languages by six well-trained and experienced research assistants, each with a master's degree.

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using smartphones. Geo-observers are deployed in their local communities, usually, at the parish level to collect and share data with the local partner university about disaster events (see Sekajugo et al. 2022).

A total of 602 agricultural households were randomly selected following multi-stage sampling (Scheaffer et al. 2006) as follows: In the first stage, two districts per region of Rwenzori and Ankole were purposively selected based on vulnerability to landslides and floods as well as coverage by the D-SiRE project. In the second stage, sixty parishes were randomly selected, forty from the Rwenzori and twenty from the Ankole sub-regions. An unequal number of parishes selected per region (and district) was dictated by project coverage. In the third stage, three villages were randomly selected per parish, and from each village 3-4 households were randomly selected following the list of the total households per village. The selection of households was not based on prior information about exposure to landslides and floods. The following number of households was surveyed in each district: Kasese (222) Bundibugyo (180) Buhweju (120) Bushenyi (80).

3.3. Empirical approach

According to the TPB, farmers are likely to express intentions to adopt DRR measures to control landslides and floods if: (1) they have a positive evaluation of the measures (attitude) mainly diversion channels and tree planting, (2) they perceive higher social pressures from relatives and friends (subjective norm) to apply the DRR measures (3) highly believe that they have control over their application (PBC). We assume that expressed intentions are triggered by the observed net benefit of the DRR measures applied on the farm (or by others) and we included actual adoption to assess such an association. Furthermore, as shown in **Fig. 2(a)**, two covariance terms are included on the dependent variables between landslide and flood models to examine if farmers' adoption behavior for landslides is correlated with that to control the spatially related disasters such as floods to investigate a multi-hazard response.

Attitude, subjective norm, PBC, and intention were measured as latent constructs, based on a Likert scale (1-5): strongly disagree to strongly agree. Each construct was examined by at least three (up to six) questions, modified from previous studies such as Anwar et al. (2020), and Lukman et al. (2021). The actual adoption of each DRR measure was assessed by one Likert scale question in which a respondent was asked as follows: I have already applied DRR measures such as tree planting and diversion channels on my farm. For each question on the TPB constructs, a respondent answered based on landslide control, and flood control separately and developed different models for the analysis of each disaster.

To investigate the impact of SIN on intentions, we developed a questionnaire based on insights from Muange et al. (2014), Murendo et al. (2018), and Jackering et al. (2019). Next, with the help of field guides, we compiled a list of actors (random match) in the respondent's network. Using the *random matching within sample approach,* applied by Muange (2015), a respondent was paired with eight network actors: three neighbors and two village administrators (representing the informal network), and three actors made of extension workers, one NGO official, and farmer organization leader (professional network). In the household survey, each respondent was asked how many times per month they talk about DRR issues in general, with each actor (member) in the informal network. As a binary response, each respondent was also asked whether they shared technical information in general with each of the actors in the professional network in the past six months, a maximum of three would be recorded if the response was positive to all professional network actors. Lastly, we examined whether a respondent was related (kinship) with the network actors in both the professional and informal network to investigate strong or weak network ties.

We hypothesize a mediation effect, in which sharing technical information with professional networks, sharing DRR information within the informal networks, and kinship influence adoption intentions through attitude, subjective norm, and PBC. Before mediation analysis[3], the classical Baron and Kenny (1986) procedure is verified following Das et al. (2021) and Azim et al. (2021): 1) before mediation, there is a significant direct effect in the path ***c*** between the predictor and the outcome variable. 2) there is a significant effect in the path ***a*** between predictor and mediator, and path ***b*** between mediator and outcome variable, after mediation, 3) after mediation, the path ***c′*** between the predictor and outcome variable should be insignificant or show a reduction in significance (or magnitude) for complete and partial mediation, respectively. Paths ***a, b, c,*** and ***c′*** are shown in **Fig. 2(b).**

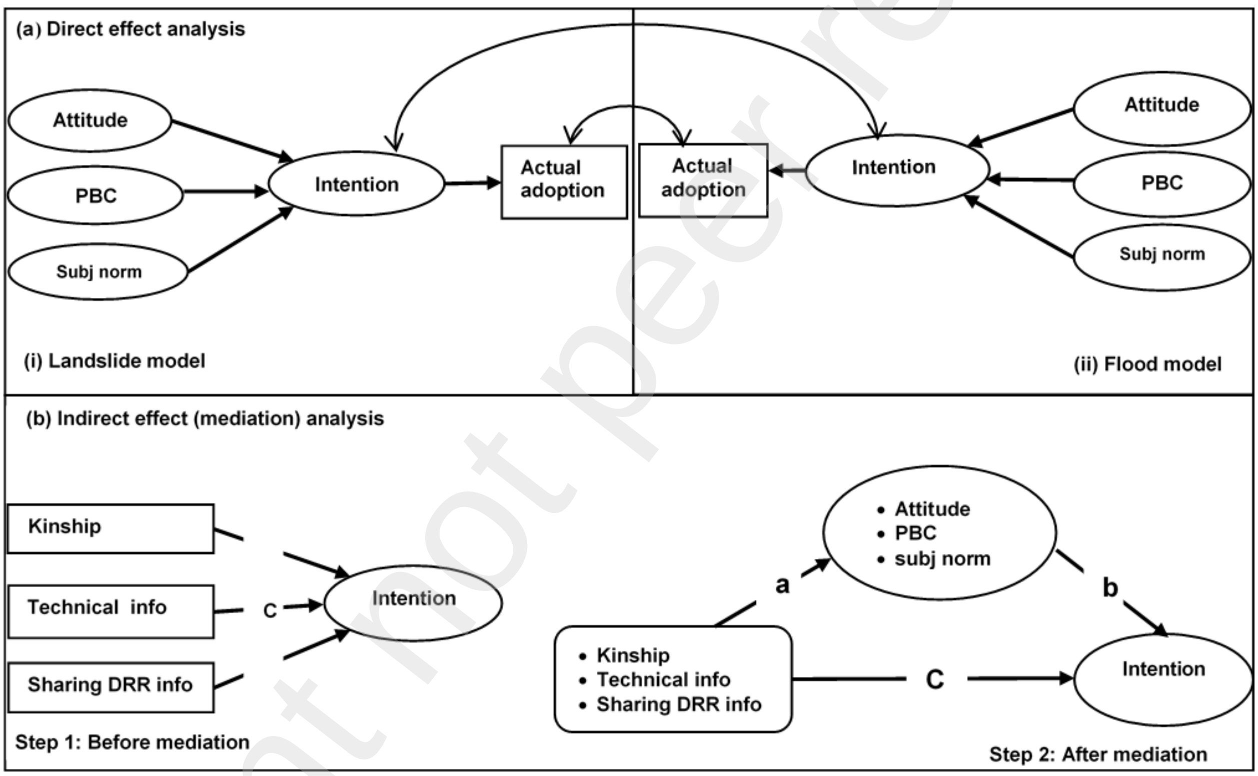

Fig. 2 Empirical model showing how the study was operationalized ***Note.*** *Acronyms; PBC: perceived behavioral control; DRR: Disaster Risk Reduction; unidirectional arrows represent Betas of the regression analysis and bi-direction arrows show correlations. For Paths,* ***a, b, c,*** *and* ***c′*** *refer to the last paragraph in the text above.*

3.4. Analytical procedure and description of the data

3.4.1 Analytical strategy

[3]We attempted to explore other pathways in which SIN can explain adoption intention in the TPB perspective such as moderation, in which an effect of the independent on the dependent variable changes with the levels of a third variable (moderator) or moderated mediation where the mediated effect changes at different levels of a moderator. Results from the two pathways were not found meaningful to explain a SIN-extended TPB. Anyone interested could read Anwar et al. (2020) and Palo and Das (2021).

Data analysis was not based on a spatial lens but on the overall picture of the area studied to explain the influence of SIN on intentions and actual adoption of DRR strategies from a TPB perspective. Structural Equation Modeling was applied using Stata 17.0. This multivariate modeling approach combines factor and regression analysis and was chosen because the dataset contained both latent constructs and observable variables (Duclos et al. 2019). Unlike classical least squares regression analysis, Structural Equation Modelling assumes that variables are measured with errors but corrects them to produce unbiased estimates (Cheung & Lau, 2017). It applies maximum likelihood estimation which is less prone to violations of Gauss-Markov's assumptions of least squares regression (Gujarati 2004). Structural Equation Modelling is also more reliable at the preparatory, actual, and post-estimation stages of data analysis (Duclos et al. 2019). It can also present the results via a path diagram whose interpretation is easy (Liu and Luo, 2018). Nevertheless, the model's assumption of no symmetric missing data, non-linearity between predictor variables, and the presence of a large sample must first be fulfilled (Stata, 2015).

3.4.2 Reliability and validity of the data

Table 1 shows the results of the exploratory factor analysis performed to investigate the structure of items per construct for a robust check of internal reliability and convergent validity (Gu et al. 2019; Bashir et al. 2020). We checked the validity using Bartlett's Sphericity test, which examines the appropriateness of inter-item correlation per construct. Next, Principal Component Analysis was applied to reduce the set of items based on principle component loading to minimize measurement errors and improve reliability (Palo and Das 2021). A Cronbach alpha test was employed to check the internal reliability (Wang et al. 2018) of the retained set of items. Further, composite reliability was calculated to measure actual composite loadings, as opposed to Cronbach's assumption that each item is equally weighted in a composite loading determination (Kabbiri et al., 2017). We calculated the Average Variance Extracted to measure the average reliability of items on the scale and show the convergent ability of latent constructs (Gu et al. 2019). To ensure the absence of divergent validity, the square root of each Average Variance Extracted value was obtained and compared with spearman's correlation coefficients among constructs (Lukman et al. 2021).

As shown in **Table 1**, Bartlett's Sphericity test results were significant ($p < 0.01$), indicating an appropriate inter-item correlation per construct. Keiser-Meyer Olkin values greater than 0.5 obtained confirm acceptable correlation and sampling adequacy. Principal Component loadings above the 0.5 thresholds were obtained (Lukman et al. 2021). Overall, construct validity was verified. The lowest Cronbach alpha value being 0.71, indicates the reliability of the scale (Wang et al. 2018). The calculated composite values were above the recommended 0.7 (Kabbiri et al., 2017). Further, the lowest calculated Average Variance Extracted was 0.51, which suggests that all the latent constructs show an ideal convergence ability (Gu et al. 2019).

Table 1. Construct reliability and convergent validity results

Survey items	Landslides					Floods				
(Based on the adoption of diversion channels and tree planting as DRR measures at the household level)	**Loading (>0.5)**	**Alpha (>0.7)**	**KMO (>0.5)**	**CR (>0.7)**	**AVE (>0.5)**	**Loading (>0.5)**	**Alpha (>0.7)**	**KMO (>0.5)**	**CR (>0.7)**	**AVE (>0.5)**
Attitudes		0.90	0.86***	0.92	0.72		0.92	0.85***	0.94	0.81
I think applying DRR measures for LS/ FL is good/ bad	0.85					0.90				
I think applying DRR measures for LS/ FL is beneficial/ harmful	0.88					0.90				
I think applying DRR measures for LS/ FL is wise/ foolish	0.90					0.91				
I think applying DRR measures for LS/ FL is (un)pleasant	0.83					0.89				
I think applying DRR measures for LS is (un)valuable	0.79									
Subjective Norm		0.79	0.73***	0.89	0.63		0.79	0.78***	0.86	0.51
People important to me expect me to apply DRR measures s for LS/ FL	0.81					0.72				
What others think I should do to reduce LS/ FL is important to me	0.83					0.73				
I would be happy if important others adopted DRR measures for LS/ FL	0.88					0.79				
I always encourage others important to me to apply DRR measures against LS/ FL	0.69					0.67				
Important others expect me to share info about DDR measures for LS/ FL	0.74					0.70				
Important others are always severely hit by disasters such as FL, which worries me.						0.68				
Perceived Behavioral Control		0.71	0.66***	0.84	0.64		0.72	0.74***	0.82	0.55
I can easily apply DRR measures to reduce LS/FL on my farm	0.82					0.80				
I can easily train others on how to apply DRR measures for LS/ FL	0.74					0.73				
I think of myself as someone who can apply the DRR measures for LS/ FL	0.83					0.76				
Only conditions beyond my control can stop me from using DRR measures to control FL						0.66				
Adoption intention		0.84	0.82***	0.89	0.68		0.87	0.83***	0.91	0.72
I intend to apply DRR measures for LS/ FL	0.85					0.88				
I wish to apply DRR measures s for LS/ FL on my farm	0.83					0.84				
I will apply DRR measures on my farm for LS/ FL	0.81					0.84				
I plan to apply DRR measures in the next 6 months for LS/ FL	0.80					0.84				
Actual adoption										
I have already applied DRR measures to my plot for LS/ FL										

Note*: n=602*, ****P <.01 for Bartlett's test for sphericity. All questions were based on a Likert scale (1-5): strongly disagree to strongly agree. Acronyms; LS: Landslides, FL: Floods, KMO: Keiser-Meyer Olkin, CR: Composite Reliability, and AVE: Average Variance Extracted. The number in parentheses in the headings of the reliability and validity parameters are thresholds.*

3.4.3 Goodness of fit of the models

Table 2 shows the results of the confirmatory factor analysis, in which we tested whether the measurement (and structural) models fit the data to determine individual items' convergence to the respective constructs (Anwar et al., 2020). The initial stage of the measurement model assessment revealed poor fit indices but some paths (individual items loading to a particular construct) were improved through modification indices (Borges and Oude 2016). Modification indices indicate the amount by which a chi-square value would be reduced if a particular parameter restriction was removed from the model (de Bérail et al 2019). Through observing the value of the chi-square, modification indices provide guidance on the paths where covariance terms can be included, which improves the model fit. The path can be improved if the modification index is significant at 0.05 and has a corresponding X^2 value above 3.841 (Borges and Oude 2016). Consequently, the results, as shown in Table 2 about major goodness of fit indices such as the ratio of the chi-square value to the degrees of freedom (X^2/df[4]), the Root Mean Square Error of approximation (RMSEA), the Comparative Fit Index (CFI), the Tucker-Lewis index (TLI), Standardized Root Mean Squared Residual (SRMR), and Pclose match the thresholds recommended in Lukman et al. (2021).

Table 2: Model fit indices for the measurement and structural models

Fit index	Threshold	Measurement model		Structural model	
		Landslide	Flood	Landslide	Flood
X^2/df	<3.00	2.427	2.219	1.939	2.249
RMSEA	<0.08	0.049	0.049	0.037	0.046
CFI	>0.90	0.980	0.979	0.978	0.974
TLI	>0.90	0.972	0.970	0.969	0.958
SRMR	<0.09	0.037	0.037	0.034	0.039
Pclose	>0.05	0.579	0.579	0.994	0.857

4. Results

4.1. Descriptive statistics

Household-specific information in **Table 3** indicates that 67% of the households were selected from the Rwenzori sub-region (33% from Ankole) guided by D-SiRE project coverage. About 87% of the household heads were male. About 68% of the household head had a primary education level and below. The average age of the household head was about 48 years old, and the average land owned by a household was about four acres. Also, about 72% of the households did farming as the main livelihood activity, the average family size was six members, and the average altitude where the homesteads were located at about 1300m above sea level.

Table 3. Household-specific information (N=602)

Variable	*Distribution*
Categorical variables	***Statistic (%)***
Gender (Household Head)	
Male	524 (87.04%)

[4] For the measurement model's X^2 value was 184.416 and the df was 76 (landslide model), and 233.068 and 105 (flood model). The structural model's X^2 value was 279.166 and the df was 144 (landslide model), and 317.221 and 141 for X^2 and df respectively (flood model)

Female	78 (12.96%)
Phone ownership by the household	
yes	498 (82.72%)
no	104 (17.28%)
Extension visit to the household	
yes	152 (25.25%)
no	450 (74.75%)
Education level of the household head	
Primary and below	409 (67.94%)
Above Primary	193 (32.06%)
Occupation (Household Head)	
Unemployed	73 (12.12%)
Farmer	436 (72.43%)
Self-employed (off-farm)	50 (8.31%)
Formally employed (off-farm)	43 (7.14%)
Respondent region	
Rwenzori	402 (66.78%)
Ankole	200 (33.22%)
Continuous variables	***Mean***
Age of the household head	47.69
Family size (members)	6.14
Land owned (acres)	3.88
Location altitude (meters)	1317.20

Table 4 shows that on average households shared technical information once with at least one of the professional network actors comprising of extension workers, training workshop trainers, or farmer organization leaders in six months before the study. A respondent shared DRR information three times per month with each of the actors in the informal network. Also, the respondent had at least two relatives among the eight actors under professional and informal networks. We also present the mean and standard deviation obtained from responses to the 5-Likert scale per set of items in the TPB constructs. An average value of 3 ('neutral') was obtained for actual adoption, compared to adoption intention's 4 ('agree') for both landslide and flood models. Spearman's rank-order correlation indicates a significant association between the main outcome variables (intention and actual adoption) and predictors (SIN and attitude, PBC, and subjective norm), except for the association between sharing DRR information within informal networks, and technical information with professional networks and actual adoption (landslide model). All off-diagonal correlations are less than the calculated values of 0.87 and 0.90 square root value of Average Variance Extracted for landslides and floods. According to Wang et al. (2018), such results show that correlations do not signal any violation of the discriminant validity and multicollinearity[5].

Table 4. Descriptive statistics, correlation matrix, and divergent validity

Model	Variable	Mean[a]	SD	1	2	3	4	5	6	7
	1) Actual adoption (5-Likert scale)	3.17	1.05	-						
	2) Intention (5-Likert scale)	3.62	0.74	0.23***	**0.87**					
	3) Attitude (5-Likert scale)	4.02	0.56	0.12***	0.56***	**0.79**				
Landslide	4) PBC (5-Likert scale)	3.70	0.71	0.19***	0.70***	0.62***	**0.80**			
	5) Subj. norm (5-Likert scale)	4.08	0.64	0.22***	0.64***	0.62***	0.69***	**0.82**		
	6) Kinship (1=relative 0, otherwise)	1.66	1.71	-0.09**	0.14***	0.12***	0.09**	0.13***	-	
	7) DRR info (informal network) (times)	2.91	2.15	-0.04	0.17***	0.22***	0.27***	0.23***	0.23***	-
	8)Technical info (prof networks) (1=yes 0 =no))	1.09	0.85	0.03	0.11***	-0.01	0.12***	0.02	0.15***	0.27***
	1) Actual adoption (5-Likert scale)	3.19	1.11	-						
Flood	2) Intention (5-Likert scale)	3.74	0.80	0.23***	**0.90**					
	3) Attitude (5-Likert scale)	4.03	0.61	0.09**	0.59***	**0.71**				
	4) PBC (5-Likert scale)	3.78	0.67	0.21***	0.73***	0.69***	**0.74**			
	5) Subj. norm (5-Likert scale)	3.77	0.61	0.17***	0.68***	0.64***	0.73***	**0.84**		
	6) Kinship (1=relative 0=no)	1.66	1.71	-0.15***	0.11***	0.08*	0.02	0.12***	-	
	7) DRR info (informal network) (times per month)	2.91	2.15	-0.08**	0.09**	0.13***	0.16***	0.22***	0.22***	-
	8)Technical info (prof networks) (1=yes 0 =no)	1.09	0.85	0.09**	0.13***	0.06	0.07*	0.07*	0.15***	0.27***

[5] Multicollinearity refers to a situation where predictors are perfect combinations of the others and result in biased estimates (Gujarati, 2004).

*Note. N=602. Values on the diagonal represent the square root of Average Variance Extracted and off-diagonal values are coefficients in a variance-covariance matrix. Significance levels: *** p < .01, **P < 0.05, *P < 0.1; [a]based on the average per category of items. The mean and Standard Deviation (SD) for sharing DRR information, technical information, and kinship are similar across the floods and landslide models because the questions were not examined based on each of the disasters separately.*

4.2. Direct effect analysis: Association between TPB constructs and intention, intention and actual adoption, and the linkage between adoption behavior for landslides and floods

The first research question examined how one's adoption intention is influenced by the TPB constructs (attitude, PBC, and subjective norm), and how intention determines actual adoption. The second question determined whether the farmer's intentions to control landslides and floods are correlated since the two demonstrate partial and temporal relations. Results for the first research question as shown in **Fig. 3** reveal that all the TPB constructs positively and significantly influence adoption intention for both landslides and floods. PBC exhibited a stronger impact, followed by subjective norm and attitude. Overall, the three TPB constructs account for 81% and 79% of the total variations in intentions to reduce landslides and floods, respectively. Furthermore, adoption intentions significantly influence actual adoption in both models (landslide: β= 0.33, p < 0.01, R^2=0.12 and Flood: β= 0.32, p < 0.01, R^2 =0.12). Though significant in all, only 12% of the actual adoption behavior is predicted by intention, suggesting an intention-behavior gap where a bigger portion of the variation in the actual adoption is not explained by the model. Fig. 3 further shows a positive and significant correlation (covariance terms) in intention (β= 1.16, p < 0.01), and that on actual adoption (β= 0.60, p < 0.01) between landslide and flood models. This is perhaps because the same location is simultaneously affected by the two disasters either happening separately or in a cascade. If someone intends/ has adopted DRR measures for landslides he is likely to express intentions/ to adopt for floods.

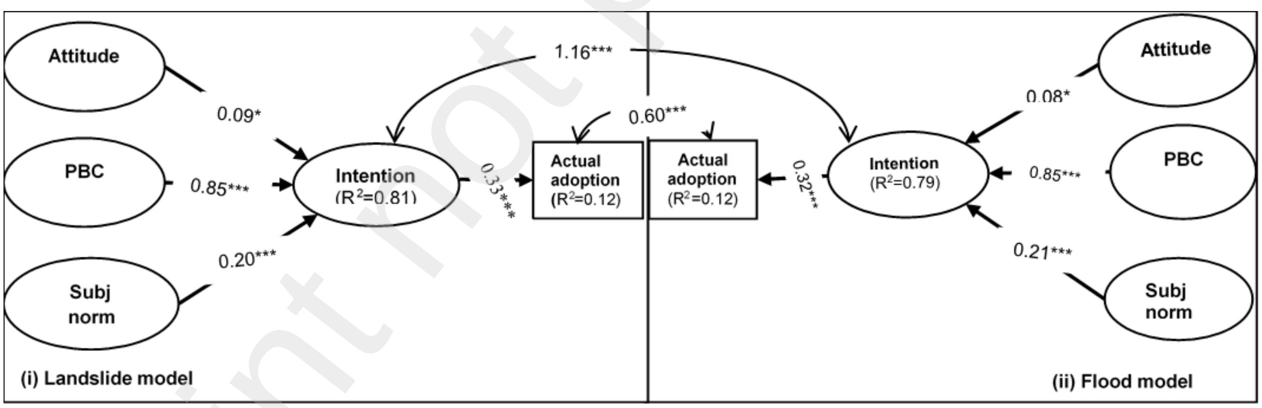

Fig. 3 Association between TPB constructs and intention, intention and actual adoption, and the association between adoption behavior for landslides and floods *Acronyms. PBC: Perceived Behavioral Control. The standardized coefficients are presented.*

4.3. Effect of social information network on adoption intention

The third objective established whether SIN variables namely, sharing technical information with professional network actors, sharing DRR information within the informal networks, and kinship determine adoption intentions, directly or indirectly through attitude, PBC, and subjective norm. In **Table 5**, all the direct relationships between SIN and adoption intention are significant, except for sharing DRR information within the informal networks in the flood model. Therefore, the latter was not included for further mediation analysis, based on the BK's mediation criteria (Mehmetoglu 2018) described in section 3.3.

Results of mediation analysis are based on the path diagram illustrated in **Fig. 2(b)**: the path between the predictor and outcome variables before mediation is given by ***c***, and after mediation the same path becomes ***c'*****,** the path between the predictor and the mediator variables is given by ***a***, and lastly**,** the path between the mediator and the outcome variables is given by ***b*****.** In the **Landslide model:** after mediation by subjective norm or attitude, the path from DRR info (informal network) to intention is no longer significant, suggesting complete mediation. Complete mediation is also observed in the path between technical info (prof networks) and intention through PBC. On the other hand, partial mediation, in which the significance level (or coefficient) reduces when a mediator is introduced, is observed between kinship and intention through attitude (c: β =0.122; $p < 0.01$ to c': β=0.035 $p < 0.01$), between kinship and intention through subjective norm (c: β= 0.122; $p < 0.01$ to c': β= 0.032; $p < 0.01$), and lastly, between DRR info (informal network) and intention through PBC (c: β = 0.130; $p < 0.01$ to c': β=-0.023; $p < 0.1$). In the **Flood model,** only the path from technical info (prof networks) to intention through PBC (c: β = 0.156; $p < 0.01$ to c': β=0.069; $p < 0.05$) and the path from kinship to intention through subjective norm (c: β = 0.114; $p < 0.05$ to c': β=0.034; $p < 0.05$) demonstrated partial mediation.

Table 5. Results of the mediation analysis

SIN variable (X)	Mediator (M)	Intention (Y)	X→Y(c)	Mediation[6] effect			
				X→M(a)	M→Y(b)	X→Y(c')	Comment[a]
Landslide model							
Kinship	Attitude	Intention	0.122***	0.031***	-0.107*	0.035***	Partial
Kinship	PBC	Intention	0.122***	0.015	1.053***	0.034**	No
Kinship	Subj norm	Intention	0.122***	0.042***	0.350***	0.032***	Partial
Technical info (prof networks)	Attitude	Intention	0.084*	-0.001	-0.099	0.041	No
Technical info (prof networks)	PBC	Intention	0.084*	0.054***	0.993***	0.056	Complete
Technical info (prof networks)	Subj norm	Intention	0.084*	0.048	0.107**	0.046	No
DRR info (informal network)	Attitude	Intention	0.130***	0.038***	-0.106*	0.011	Complete
DRR info (informal network)	PBC	Intention	0.130***	0.044***	0.991***	-0.023*	Partial
DRR info (informal network)	Subj norm	Intention	0.130***	0.103***	0.110**	-0.006	Complete
Flood Model							
Kinship	Attitude	Intention	0.114**	0.032**	0.024	0.028**	No
Kinship	PBC	Intention	0.114**	0.015	0.452***	0.020	No
Kinship	Subj norm	Intention	0.114**	0.045**	-0.162***	0.034**	Partial
Technical info (prof networks)	Attitude	Intention	0.156***	0.053	0.022	0.072	No
Technical info (prof networks)	PBC	Intention	0.156***	0.052**	0.440***	0.069**	Partial
Technical info (prof networks)	Subj norm	Intention	0.156***	0.037	-0.173***	0.087	No
DRR info (informal network)	Attitude	Intention	0.035				
DRR info (informal network)	PBC	Intention	0.035				
DRR info (informal network)	Subj norm	Intention	0.035				

Note. *Acronyms; PBC: Perceived Behavioral Control, DRR: Disaster Risk Reduction. Technical info (prof networks): Sharing technical information with the professional networks and DRR info (informal networks): Sharing DRR information in the informal networks. Significance levels: *** p < .01, **P < 0.05, *P < 0.1. Standardized coefficients are presented.* [a]*Complete mediation is when the significance of a direct path between the predictor and outcome disappears after mediation, suggesting that all the direct effect goes through the indirect path; partial mediation is when the significance (or magnitude) of the direct path between the predictor and outcome reduces after mediation, suggesting part of the effect goes through the indirect path; no mediation means any of the partial and complete mediation conditions is not reflected. DRR info (informal network) in the flood model did not pass BK's first step mediation criteria and was excluded from the mediation analysis*

5. Discussions and conclusions

[6]Mediation is based on Baron and Kenny's approach obtained using the 'medsem' command explained in Mehmetoglu (2018).

5.1. Discussion and implications

This study focused on a social information network-extended application of the TPB to explain the drivers of smallholders' intention and actual adoption of DRR measures against landslides and floods. The classical TPB has been widely applied in health sciences, social media, crime, and social justice studies in western cultures (Sanne and Wiese 2018; de Bérail et al. 2019; Caffaro et al. 2019; Pérez-Macías et al. 2020; Feng et al. 2021) but has scarcely focused on the adoption behavior of farm-level DRR measures in developing countries. By explaining 80% of variations in the intentions, this study demonstrated that TPB is plausible in predicting smallholder farmers' adoption behavior for DRR measures in the Rwenzori and Ankole in Western Uganda, the sub-regions typical of a disaster-prone rural setting in a developing country. Among all, PBC being the main determinant of intention is consistent with other studies (Dwidedi et al. 2012; Das et al. 2021). Gaining greater control over behavior is an important step in the process of social change for sustainable environmental management (Caffaro et al., 2019). Policy-makers should ensure institutionalized communication and regular training to enable farmers to perceive the adoption of DRR strategies as being under their volition control. They should also ensure participatory needs assessment, designing, and implementation of DRR programs that alleviate limitations of adoption.

Perceived control of the adoption of DRR measures comes in several forms: understanding the nature of the disaster, knowing how to apply the measure, and having access to materials. However, during field interactions, farmers in the study area still lack adequate knowledge due to limited access to information targeted to DRR, which is consistent with the study by Mertens et al. (2018). A significant role played by subjective norm is quite intuitive given the nature of rural settings in developing countries with a strong social network (Caffaro et al. 2019). Household interdependence is not only manifested in sharing of tools, social labor, food, shelter, and seed but also in the sharing of information, and learning by observing the practices of neighbors. Once the practice starts to be adopted by many, this leads to subjective norm that lead the less convinced farmers to also adopt it. The influence of attitude on adoption intentions is positive and significant, suggesting that farmers who view the outcome of adoption more favorably are likely to express intentions. As suggested in the study by Daxini et al. (2019), farmers' attitudes are less important than their perceived ability and social pressures. However, this study highlights the need to gain insights into how one's attitudes determine effective adoption and suggests that the underlying critical factors that promote positive attitudes toward adoption should be considered when designing policy measures.

Both descriptive statistics and structural equation modeling revealed higher intentions being expressed than actual adoption of DRR measures for both landslides and floods, suggesting the intention-behavior gap described in other studies such as Al-Debei et al. (2013), Pérez-Macías et al. (2020), Yang and Wu, (2021) and Feng et al. (2021). Such a gap could partly be explained by the limited technical ability, lack of trust in the measures towards stronger disaster events, and shortage of supplies related to DRR measures in cash-strapped rural settings (Mertens et al. 2016; Arunrat et al. 2017). Strategic policy interventions should target such constraints and promote rural finance schemes and tree nurseries. Stronger regular floods associated with major rivers in the area like Nyamwamba, and Humya, overpower smallholders' adaptive efforts. Capital- and technical-intensive DRR strategies such as mapping disaster hot spots and protecting riparian forest buffer zones are best implemented by the state (Huang et al., 2022;

Podgornov et al., 2021). The government should also undertake investment in infrastructures such as maintaining the river channels through dredging, building stronger and broader bridges, and environment protection through enforcement of proper land use practices.

Households in the study area are simultaneously at risk of multiple interacting disasters that generate synergies or cascades. A multi-hazard impact of landslides and floods could be explained by the spatial, cascading temporal relationship. Sometimes, flooding results from landslide debris blocking the natural water channels, and the accumulated water is diverted or released at once hence overpowering the natural channel (Jacobs et al., 2016). Thus, response to such disaster risks might demonstrate a similar multi-hazard interaction. As revealed by this study, both intention and actual adoption of DRR measures against the two disasters are highly correlated. From our field experience, most farmers buy small land parcels in lowland areas perceived as less risky of disasters to establish homesteads. They use plots on the steep slopes for farming activities. They also choose lowland areas for settlement because the highlands are under-supplied with transport and communication systems, water, education, and health facilities. Therefore, in parallel to the intention to apply strategies like tree planting to protect their homesteads from floods, they also plan to protect their plots located on steep slopes from landslides. The result could also be explained by the fact that farmers who intend to or adopt a measure for one disaster are likely to be those with control over the adoption behavior in terms of resources and skills or generally have more positive attitudes PBC and subjective norm which are associated with intention to adopt strategies in general. The findings suggest that policy-makers should consider such interactions at each stage of planning and resource allocation, and not underestimate spatially related disaster risks, which is in agreement with Gill and Malamud (2016). The result also suggests policy interventions that focus on providing comprehensive, fully packaged training on DRR in general, not specific to a single hazard.

The social information network (SIN) presents great potential to increase access to information in rural areas in developing countries experiencing a digital divide discussed by Kabbiri et al. (2017). Moreover, all our results indicate a significant direct effect of SIN variables on adoption intentions. Overall, sharing technical information with professional network actors had a comparatively higher direct effect (flood model) but sharing DRR information within the informal networks had a higher impact under the landslide model. This is perhaps because of an idiosyncratic shock, where, compared to floods, landslides show localized impact, affecting few households at a time, and information sharing and help are sought from the immediate networks. Overall, the result suggests that both networks should be complementary, thus, informal networks cannot substitute the role played by formal training programs. The main setback of the informal networks is that actors possess identical ideas and lack of a technical grasp of the innovation due to limited information exchange (Caffaro et al., 2019). As concluded by Muange et al. (2014) in their study on social networks and exposure to improved varieties in Tanzania, informal networks can support but not replace formal extension programs. The need to promote both networks is necessary because not all farmers attend formal training workshops and share the information effectively. The study findings also suggest the need to ensure that information spread in informal social networks is of higher quality by training targeted individuals in the network so that they become more knowledgeable.

Results from mediation analysis confirm that the more information is shared in the social network, the higher the household's PBC, and a more favorable attitude, which then leads to a higher intention to adopt DRR measures. The indirect effect of SIN on intention through the TPB constructs is more significant for landslides, suggesting that more adoption behavior for landslides is driven by perceptions based on social networks. Since landslides do not affect many households at once, their DRR behavior does not spread to many at the same time, so the word of mouth might be more important in influencing perceptions and intentions. The results also confirm our hypothesis that the TPB constructs do not just influence adoption intentions directly but play some role in mediating other determinants of intention. Further, the results show that the stronger the network ties (kinship) the more intentions are expressed based on the subjective norm. Also, subjective norm mediated the effect of sharing DRR information within informal networks on intention in the landside model. Most land-use decisions and access to supplies such as tools and tree seedlings in developing countries largely depend on family ties and social links (Ramirez 2013). Policy interventions should focus on how to exploit such social links through establishing disaster sensitization campaigns such as disaster rescue teams, community video groups, and drama groups. Through such collaborations and learning effects farmers' attitudes and perceived control significantly improve which shapes adoption behavior.

5.2. Limitations of the study

While the study posits several theoretical and practical implications, two main weaknesses are highlighted. First, the study analyzed cross-section data and thus, assessed the association between the key variables such as SIN, intention, and actual adoption. Such a design is limited in testing the causal-effect relationship and lacks generalization for causal links (Das et al. 2021). Further research could apply the longitudinal design using information-treated social networks delivered in randomized control trials. Second, we collected data about SIN using the *random matching within sample approach,* involving eight members from a random sample in the social network. Though representative of the typical individual's network, the method is costly when dealing with a large population (Muange et al., 2014). It also tends to leave out other respondents' social links that span out geographically or are unreported. Further studies should apply other theoretically appealing and cost-effective methods such as paired-actors (dyads) (Jackering et al., 2019), in which a respondent name their social links.

5.3. Conclusions

This study developed an empirical model based on Structural Equation Modelling to investigate the role of social information networks in explaining farmers' adoption behavior against landslides and floods from a TPB perspective. Attitude, subjective norm, and PBC significantly explain adoption intention but less of the intention expressed turns into actual adoption, revealing the intention-behavior gap. The intention to adopt DRR measures largely depends on PBC, suggesting the need for institutionalized regular training and revamping rural finance schemes to enable farmers to perceive adoption as being under their volition control. Also, farmers' DRR efforts follow a multi-hazard interaction, in which adoption behavior for landslides and floods are directly correlated. The design of policy and resource allocation should also demonstrate such a multi-hazard interaction, without underestimating spatial and temporal consequences. Farmers' social information networks matter in explaining adoption intentions, both directly and indirectly. The study has shown that PBC, attitude, and subjective norm also play a significant role in mediating the effect of SIN on adoption intention. Overall, PBC was the most significant determinant, both directly and indirectly through the mediation of the effect of sharing technical information with professional networks on adoption intentions. Both professional and informal networks significantly determining adoption intention suggests that the role of extension services cannot be substituted by informal social networks but the two should be complementary. Since landslides do not affect many households at once, SIN's effect on intention through TPB constructs is more significant for landslides suggesting that most of the adoption behavior is driven by perceptions. The findings provide strategic policy lessons and pave way for further research on how professional and informal networks can be organized to improve access to technical and timely information from peers to enhance farmers' PBC (self-efficacy), which is key in determining the intention to adopt DRR measures for improved livelihoods.

Statements and Declarations

Funding

We appreciate VLIR-UOS for funding this research through the TEAM project (UG2019TEA492A105): Digital citizen science for community-based resilient environmental management (D-SiRE) implemented by Vrije Universiteit Brussels and KU Leuven, Mbarara University of Science and Technology and Mountains of the Moon University.

Competing Interests

All the authors declare no conflict of interest either through affiliations or involvement in any organization with any financial or non-financial interest related to the subject matter discussed in this manuscript.

Author Contributions

All authors contributed to the study conception and design of the study. Rodgers Mutyebere: material preparation, data collection, analysis, writing the final manuscript. John Sekajugo, Clovis Kabaseke, Grace Kaor-Rugunda, Ronald Twongyirwe, Matthieu Kervyn and Liesbet Vranken: gave critical reviews and comments at every stage of writing. All authors read and approved the final manuscript.

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Does the farmer's social information network matter? Explaining adoption behavior for disaster risk reduction measures using the theory of planned behavior

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