

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

Rodgers Mutyebere^{a,b,*}, Ronald Twongyirwe^c, John Sekajugo^{d,f}, Clovis Kabaseke^d, Grace Kagoro-Rugunda^e, Matthieu Kervyn^f, Liesbet Vranken^a

^a Department of Earth and Environmental Sciences, KU Leuven, Leuven, Belgium

^b Department of Agricultural and Resource Economics, Mountains of the Moon University, Fort Portal, Uganda

^c Department of Environment and Livelihoods Support Systems, Mbarara University of Science and Technology, Mbarara, Uganda

^d Department of Environmental and Natural Resources, Mountains of the Moon University, Fort Portal, Uganda

^e Department of Biology, Mbarara University of Science and Technology, Mbarara, Uganda

^f Department of Geography, Vrije Universiteit, Brussels, Belgium

ARTICLE INFO

Keywords:

Theory of planned behavior
Disaster risk reduction measures
Structural equation modeling
Adoption intention
Landslides
Floods

ABSTRACT

Smallholder farmers' vulnerability to climate-related disasters in Sub-Saharan Africa is increasing, partly due to land-use changes and poor adoption behavior for Disaster Risk Reduction (DRR) measures. Such behavior can be explained by poor beliefs about DRR measures due to limited access to information. Agricultural extension workers are increasingly less trusted because they tend to transfer information less targeted to DRR and have limited spatial coverage. We apply the Theory of Planned Behavior (TPB) to explain the adoption behavior for DRR measures and further investigate whether Social Information Networks (SIN) explain the behavior beyond the TPB determinants. 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 (SEM) demonstrate that TPB explains the adoption behavior with Perceived Behavioral Control (PBC) as a stronger driver of intentions than subjective norms and attitudes. The intention to apply DRR measures is significantly associated with actual adoption. Farmers' behavior to control landslides and floods is correlated because the same location is at risk of such interacting disasters. Moreover, SIN also significantly predicts adoption intentions through the three theoretical predictors by playing a moderating role. 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 share information with farmers.

1. Introduction

Climate change has shaped the debates at global level to generate ideas for adaptive land-use policy and practices [1]. The impetus is provided by the evidence: between 1970 and 2019, climate change-related disasters accounted for 91% of global disaster events,

* Corresponding author. Department of Earth and Environmental Sciences, KU Leuven, Leuven, Belgium.

E-mail addresses: rodgers.mutyebere@kuleuven.be, mutyrodgers@gmail.com (R. Mutyebere).

with hydrological disasters such as floods and landslides accounting for about 45% [2]. While the two disasters tend to happen separately, they can occur as cascades where a primary disaster such as landslides triggers secondary disasters like floods due to the debris flow blocking natural water channels leading to dam formation [3,4]. According to CRED and UNDRR (2021), the effect of floods and landslides is heavily felt in Africa, whereby over 1200 deaths were recorded and seven million people affected in the period between 2006 and 2019. 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 (compared to 0.2% for developed) countries since 2006 [5]. High population is associated with high demand for agricultural land which increases the degradation of fragile ecosystems vulnerable to disasters [6]. Therefore, farmers are both key contributors and the most affected by disasters [7] and should thus lead in the implementation of farm-level Disaster Risk Reduction (DRR) measures [8].

Risk management and vulnerability reduction (i.e., DRR measures such as tree planting and diversion channels) are among the most recommended and popularized measures for smallholders [8]; Mugonola, 2013). While diversion channels represent structural and hazard specific DRR measures, tree planting is a biological measure that can deal with multi-hazard impacts [9,10]. The two can be applied together or further with several farm-based soil conservation practices such as contours, terraces, ridges, and grass strips. Surprisingly, poor adoption behavior for such important measures by smallholder farmers in Uganda vulnerable to disasters is still reported [7]. There is also evidence from developed counties where farmers have not adopted sustainable innovations even when their economic status indicates they should [6], and the cost-benefit models seem not sufficiently explain such behavior.

To understand and predict behavior, the Theory of Planned Behavior (TPB) – a reasoned action approach [11] is well-known and has been applied in several studies such as [12,13]. TPB postulates that social-psychological constructs, namely attitude, subjective norms, and Perceived Behavioral Control (PBC) are the theoretical determinants of behavior through intentions [14]. Nonetheless, [15] pointed out the theory's limited capacity to explain behavior by failing to account for the intention-behavior gap. As a result, some studies have applied an extended TPB beyond the three theoretical determinants. [16] extended the TPB through network ties, and shared language to explain entrepreneurship behavior, while [17] extended the TPB through social media exposure to health information to explain the protective behavior against air pollution, and both extensions improved the theory's predictive power. However, it remains unclear whether access to information influences the farmers' adoption behavior for DRR measures and can provide further explanation on the adoption behavior beyond the TPB determinants of behavior. In this study, the focus on information is critical because the beliefs held by farmers about adoption of DRR measures could be influenced by the kind and source of information they are exposed to.

Limited access to information is one of the challenges faced in the adoption of most agricultural technologies [18,19], yet [20]'s adoption of innovation's theory emphasizes access to information to improve adopters' awareness. As such, the Sendai framework¹ on DRR recommended that farmers' resilience to disasters should be strengthened through providing relevant information [21]. In rural settings in developing countries, information is obtained from agriculture extension workers, social media, and social networks. Though, in rugged terrains experiencing rural-urban divide due to poor roads, internet and electricity connections, social networks present an invaluable alternative for most households [22,23]. Whereas [24] classifies social networks as either informal or professional networks, [25] further categorizes the networks into either being based on kinship, or on work relations and affiliations and describes them as strong and weak networks, respectively. Professional networks (e.g. Agriculture extension workers) typically deliver technical, novel, non-redundant but general information that covers perspectives and issues from a wider geographical area, which might have less influence on one's attitude compared to informal intra-village social networks that transfer more targeted information [6].

Social networks are a form of social capital consisting of individuals interacting consciously to aid in the sharing of resources [23]. When social networks help in information sharing, they can be referred to as Social Information Networks (SIN) [26]. An understanding of how SIN explains adoption of DRR measures is necessary because when affected by disasters, most people in developing countries do not only reach out to professional networks such as extension workers for information regarding DRR measures, but also turn to relatives, neighbors, and friends. There is a dearth of studies that examined the factors that influence the adoption of DRR strategies, interrelationships in disaster control behavior and how SIN explains DRR strategies' adoption in a developing country. Therefore, this 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 behavior? (2) Considering the temporal and spatial relations, is there an interrelation between the intention to control landslides and intention to control floods? (3) Does the farmer's SIN moderate the relation between the TPB constructs or influence adoption intentions indirectly through attitude, PBC, and subjective norm? To answer these questions, we apply Structural Equation Modelling (SEM) and hierarchical regression to analyze cross-sectional data collected in October 2020 from 602 agricultural households in the Rwenzori and Ankole sub-regions in Western Uganda. In the next section, we elaborate on the TPB constructs, and describe the empirical approach, the study area, sampling, and analytical procedure in section 3. In section 4 we present the results while discussions and conclusions are given in section 5.

¹ 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. It focuses on the development agenda that provides the Member States with concrete actions against disaster risks.

2. Theoretical framework: Theory of planned behavior

Conceptually, behavior refers to an individual's actions, usually preceded by strong intentions [11]. Intention is an anticipated outcome that guides planned actions and indicates how much someone is willing to invest to perform a behavior [14]. It should be noted that predicting intention is quite complex: it is driven by extrinsic factors such as socio-demographic attributes, and intrinsic factors like social-psychological aspects such as attitude, subjective norm and PBC, which are highly unobservable [27]. Evolving from the theory of reasoned action [14], TPB was proposed to explain social-psychological behavior. According to [11]; TPB postulates that intention is influenced by three constructs. (1) Attitude, which is inextricably linked to personal beliefs and one's evaluation of whether a behavior is positive or not. (2) Subjective norm, which refers to perceived social pressure from others considered important such as family and friends. (3) PBC, which refers to one's perceived ability to engage in or have volitional control over a behavior and it is a proxy for actual control when the latter cannot be accurately measured [28].

Other things equal, the more favorable the attitude and subjective norms are, and the greater the PBC is, the stronger should be the intention to perform a behavior [11,14]. Also, the stronger the intention, the more likely behavior will be performed. [11,29] argued that most people must have volitional control over a behavior for intention alone to sufficiently predict behavior. With incomplete volitional control (e.g., lack of requisite skills or resources like land and capital), examining the direct effect of PBC on actual behavior might improve the prediction [30]. Further, in the initial formulation of the reasoned action approach and the TPB, subjective norm was defined in terms of what important others think about performing a behavior [14]. However, [11,29] suggest the need to explore further the two subdimensions of subjective norms: injunctive norm, concerned with the perceptions (desires) of important others about whether (or not) we should perform a behavior, and descriptive norm, which refers to perceptions (actions) that others are (not) performing a specific behavior.

To ensure stronger inter-indicator and indicator-to-construct correlations required in reflective measurement models [31,32,33], one of the fundamental requirements is strict adherence on the principle of compatibility in the formulation of the measures. According

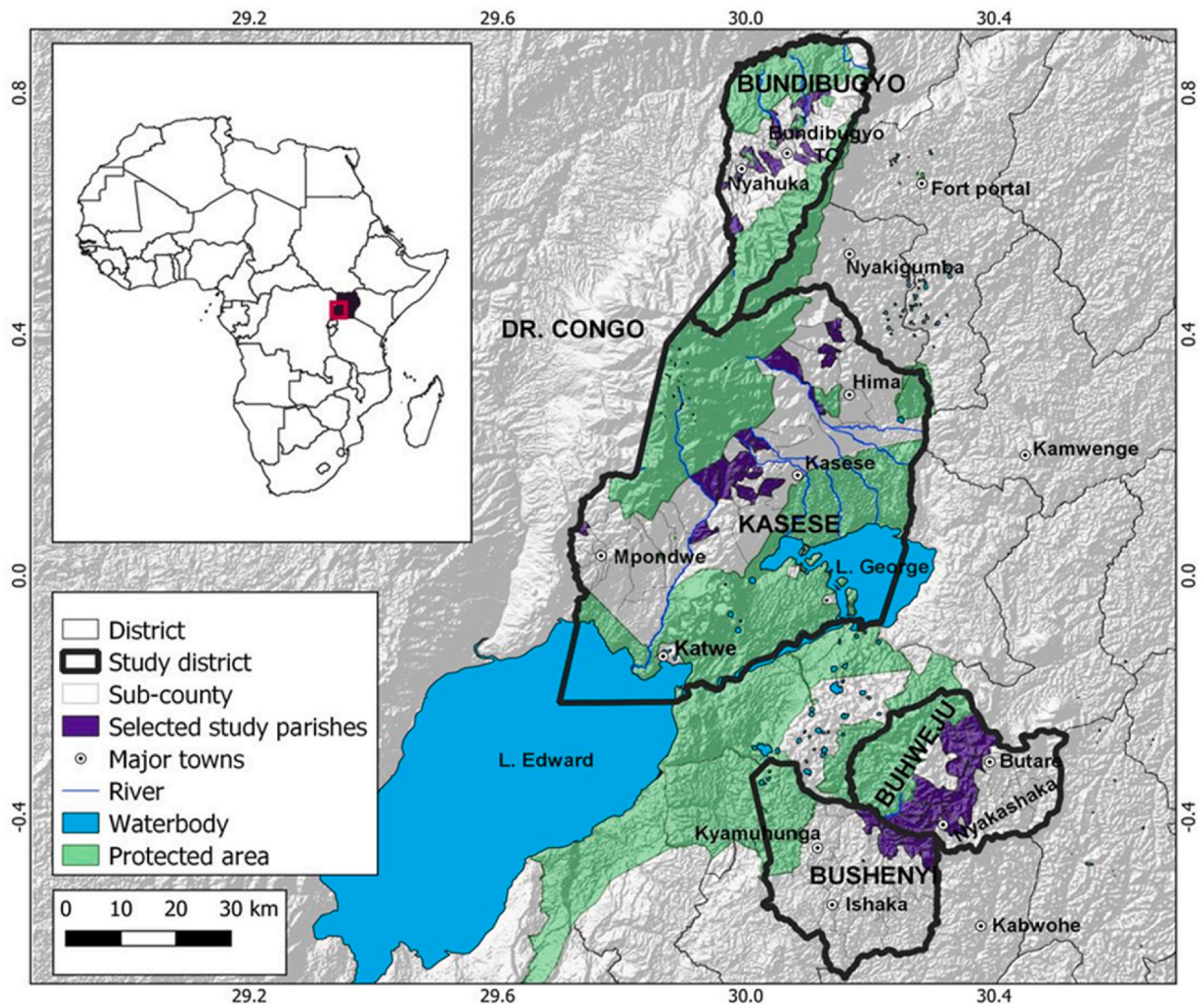


Fig. 1. Location of the study districts showing parishes covered

to [11]; compatibility can be described as: (1) behavioral compatibility, which is concerned with how behavior is defined by the measures of intention, (2) scale compatibility, which emphasizes that the scales used to measure intentions should be compatible, and (3) category compatibility, which requires the criteria constituting the behavioral categories to be compatible. The principle of compatibility further stresses the need to define and assess all the TPB constructs that measure a given behavior in terms of the target (T) a given behavior is directed to, action (A) to be performed, context (C) in which the behavior occurs and the time (T) period, also known as the TACT Principle [34].

As a major shortcoming, TPB framework only recognizes that the cognitive beliefs (attitude, subjective norm and PBC) are formed by background factors but does not specify the origins of these beliefs in the model. Instead, it indicates that the choice of such variables is an empirical question [29,14]. According to [11]; background factors such as socio-demographic factors, information, and social networks potentially influence the beliefs and categorize these beliefs into being observational, inferential, and informational based on how they are formed. The current study focuses on informational beliefs and argues that people hold beliefs about the adoption of DRR measures depending on the information they are exposed to. Moreover, the individual level measure of information is expected to correlate with the position they hold in the social structure [11], which might also explain adoption behavior.

[34] presented several ways in which background variables were inserted in regression models. Most studies applying the TPB collect information about background factors and only use it to describe sample characteristics, while others use it to segment the population to compare subgroups, and others (e.g. [16] include them in the models as control variables. Moreover, [14] indicated that, apart from attitude, subjective norm, and PBC, other factors can only influence behavior when mediated by the three constructs. A few studies like [12,35] have investigated the possible moderator-interactions involving background factors beyond the independent effects of the TPB constructs. However, in their recommendations, [35] underscore the need for researchers to go beyond simple additive modelling of TPB cognitions and account for a third-variable effect, suggesting mediation analysis. [30,36,37] and [38] have explicitly investigated the proposition that the effects of different background variables are mediated by the theoretical determinants of intention and the results obtained range from no mediation to complete mediation. Social information networks, like other background factors, are expected to influence intentions indirectly by their effects on the theory's more proximal determinants [39]. As such, [16] found that the effect of network ties on students' entrepreneurship intentions is mediated by the TPB constructs. Whereas, [] combined mediation and moderation analysis to examine the role of information accuracy in the prediction of behavior in the TPB framework.

3. Materials and methods

3.1. Study area

Uganda is in the tropical region of Africa (Fig. 1). Specifically, the study was carried out in the Western Uganda districts of Kasere (0.06°N, 30.06°E) and Bundibugyo (0.68°N, 30.02°E) in the Rwenzori Sub-region, and Buhweju (0.29°S, 30.29°E) and Bushenyi (0.48°S, 30.20°E) in the Ankole Sub-region. The sub-regions are vulnerable to landslides and floods due to their location on the slopes or flood plain of the Rwenzori Mountains, Uganda's highest mountain (5109m above sea level), characterized by incised valleys upstream, sharply transitioning to flat lowland downstream [40,41,7,42]. Since topography (represented by the slope angle in the figure) is one of the factors controlling landslide occurrence [43] and the area is inhabited by smallholder farmers [42], it is an interesting case study area for farmers' adoption of DRR measures.

The study area also receives a high bi-modal orographic rainfall, about 1540mm [44], induced by the convection of moist areas of the Congo Basin [3]. It is supplied by several rivers such as Nyamwamba, Nyamugasani, Rubilhiha, and Humya which are associated with frequent flooding, and lakes George and Edward cover the lower part of the Rwenzori Mountains. The four districts were selected because they are covered by the D-SiRE² project (2019–2023), which played a key role in mapping the disaster hot spots. The study focuses on landslides and floods due to their high occurrence and socio-economic consequences in the country. For example, between 2010 and 2019, landslides accounted for up to 1500 annual fatalities, while flooding alone affect over 50,000 people annually through death, displacement, and loss of property (WB & GFDRR, 2019).

3.2. Survey procedure

Two Focus Group Discussions (FGDs) per district were conducted comprising of ten respondents identified with the help of a community development officer and gathered in a convenient meeting place. Based on the anticipated technical ability and experience, we selected one agriculture extension worker, a parish chief, two village chairpersons, a citizen scientist, and five farmers (male and female) for each focus group. To conduct the FGD, we followed the steps proposed by [45] regarding the preparatory, actual, and post-session practices. A well-moderated discussion using moving debate focused on the pre-developed questions [46]. TPB constructs, awareness and information sources, climatic factors, and institutional factors as drivers of the adoption of DRR measures were discussed. The frequency of responses per question was counted and recorded as emphasized by [11]. The results of the FGDs helped in the questionnaire development and provided insights in the general understanding of the results of the quantitative analysis. The questionnaire was then delivered to the respondents using SurveyCTO software on android 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 improve clarity and reduce the length of the questionnaire. Face-to-face interviews were conducted in the local language by six well-trained

² D-SiRE in full, is Digital citizen Science for community-based Resilience on Environmental management. It is a TEAM project under VLIR-IOUS, in which citizen scientists known as geo-observers are recruited on recommendation by the local community, and trained in reporting disaster events 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 [83]).

research assistants, each with a master's degree.

A total of 602 agricultural households were randomly selected following multi-stage sampling [47]. Two districts per sub-region of Rwenzori and Ankole were purposively selected based on vulnerability to landslides and floods, and coverage by D-SIRE project. Then, sixty parishes were randomly selected, forty from the Rwenzori and twenty from Ankole sub-regions. Further, three villages per parish, and 3–4 households from each village were randomly selected following the list of households obtained from the respective village chairpersons. The household number per village was not proportional to the village size but was determined by logistical and time constraints rather than statistical procedure and was not based on prior information about exposure to disasters. The following number of households were surveyed per district: Kasese (222) Bundibugyo (180) Buhweju (120) and Bushenyi (80).

3.3. Empirical approach

In the TPB framework, farmers are likely to plant trees and/or dig diversion channels (DRR measures) the next rainy/planting season (intention) to reduce landslides and floods if: (1) they have a positive evaluation of the DRR measure (attitude), (2) they perceive higher social pressures from referents (e.g. family, friends and colleagues) to apply the measure (subjective norm³), and (3) highly believe that they control the process of the measure's application (PBC). Therefore, attitude, subjective norm and PBC are usually regressed directly on intention as shown in Fig. 2(a). According to [11]; intention can independently permit a good prediction of behavior without accounting for PBC's direct effect on the behavior if individuals have volitional control over a behavior. However, due to land, capital and technical differences among farmers, volitional control over the adoption of DRR measures might vary, and as such it is recommend to regress PBC directly on behavior in addition to being mediated by intention [29,11].

Attitude, subjective norm, PBC, and intention were assessed 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 as guided by Ajzen (2019) and [11]. To measure the latent constructs, each respondent answered on landslides and floods separately. Actual adoption of each DRR measure was assessed by one 5-Likert scale question (“strongly disagree” – “strongly agree”) in which a respondent was asked as follows: I have already applied the DRR measure (either planting trees to control landslides or diversion channels to control floods) on my farm. Furthermore, as shown in Fig. 2(b), a covariance term⁴ is included between intention and actual adoption under landslide and flood models to investigate whether hazard interaction also triggers interaction in the adoption behavior for DRR measures. This is pertinent as the spatial and temporal relations between the two disasters might influence farmers' land-use decisions [48] and such knowledge helps to avoid underestimating the risk at disaster escalation points and the resultant spatially related disasters.

To investigate the indirect impact of SIN on intentions, we included questions in the survey based on insights from Muange et al. (2015), [26]; and [49]. By the help of field guides, we compiled a list of people (random matches) in the respondent's network. Using the random matching within sample approach, applied by [50]; a respondent was paired with nine individuals in the network: three immediate neighbors, one distant village member, two village administrators (informal network), and three people from the professional network (extension worker, one NGO official, and farmer organization leader). In the survey, each respondent was asked how often they talk about general DRR issues (per month) with each selected member in the informal network (Sharing DRR informal). Each respondent was also asked if they shared technical information (Technical info) with each of the selected professional network members in the past six months. We also examined whether a respondent is a close relative to each of the selected network members (Kinship) to investigate strong or weak network ties.

Other than SIN, other background factors such as socio-demographic and regional characteristics might also influence farmers' adoption decisions and when included in the model they might alter the regression outcome but are not of direct interest to the study [11]. To control the spurious effect attributed to model overfitting [51], the influence of such unaccounted variables enters the error term. Nonetheless, following other studies like Jafarkarimi et al. (2016) and [52]; we included some control variables such as household head's age and gender, income, land size, and geographical region. A significant gender bias in information was observed in a study by Muange et al. (2015), where women were more informed about improved sorghum varieties. Age also determines the kind of information shared in the network [16]. Region was included because topographical differences influence land use dynamics and exposure to disaster risk [53]. While we could associate large landowners with adoption of DRR measures due to the land incentive to meet both economic and conservational objectives, [54] observed land-constrained households as the most likely to apply DRR strategies and indicated income as a major constraint.

We analyze the effect of SIN on adoption intentions both as moderator and mediator variables in the TPB framework as shown in Fig. 2(c).

3.4. Analytical procedure and data reliability

3.4.1. Analytical strategy

Before analysis, data screening was conducted to check and correct errors to ensure data reliability. Errors like missing data arise due to item-nonresponse or careless recording by enumerators. [55] has suggested that <5% of missing data should be of little concern

³ In this study we used the conventional term subjective norm, which refers only to injunctive norms, because one's perception may (not) reflect what the important others (referents) think, desire, or expect him/her to do [11].

⁴ In this study we only examined the correlation using the covariance term in a recursive model instead of a feedback loop commonly applied in non-recursive models to avoid problems of identification and endogeneity [61]. Theoretically, all non-recursive models suffer from endogeneity problem, in which the explanatory variable is correlated with the error term of the dependent variable, and thus cannot reliably be estimated without instrumental variables (IV) [84]. At the time of analysis, we did not find the right IV that would meet the key assumptions of instrument strength and validity.

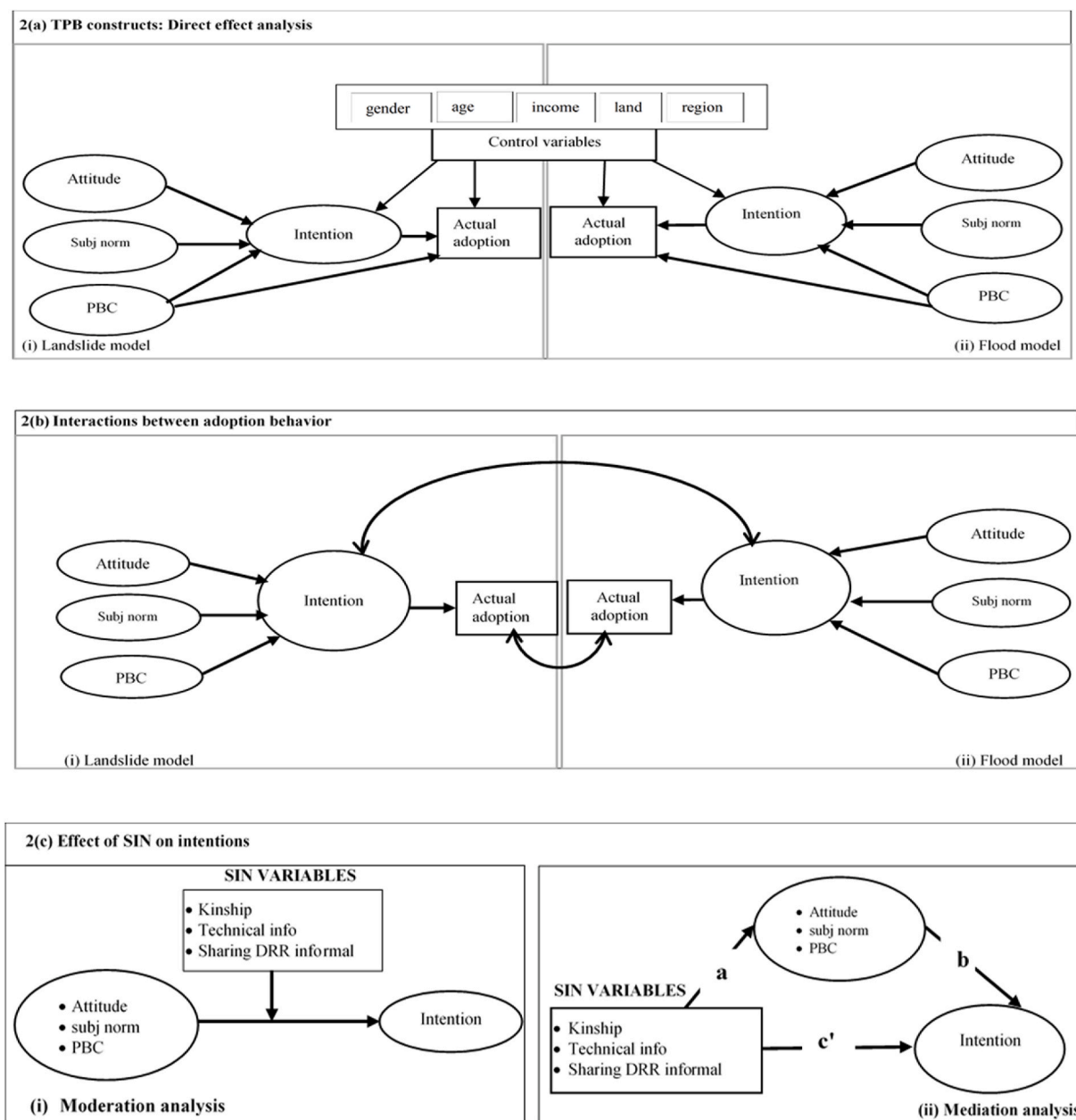


Fig. 2. Empirical models. Note. Acronyms; PBC: Perceived Behavioral Control; Subj norm: subjective norm; DRR: Disaster Risk Reduction; SIN: Social Information Network; Technical info: sharing technical information from professional networks, Sharing DRR informal: sharing any information in the informal social network. unidirectional arrows represent direct influence and bi-direction arrows show correlations.

but any higher figure should be investigated. While some studies apply ad hoc techniques such as pairwise deletion and mean and median imputations [55,56] to fix the incomplete data, such methods underestimate the variance-covariance structure [57]. In our data, subjective norm and income had 15% and 18%, respectively of data missing and we applied Maximum Likelihood Estimation (MLE) with missing data estimation in SEM which solves the problem through model simulations which does not distort the variance-covariance structure [57].

Data analysis was not based on a spatial lens but on the overall picture of the area studied. SEM was applied using Stata 17.0 in the two-step approach. First, we evaluated the measurement model using Confirmatory Factor Analysis (CFA) to determine the loading of indicators per construct. Second, we estimated the structural equation model for the causal relationships. SEM as a multivariate approach combines factor and regression analysis and was chosen because the dataset contained indicators of latent and observable variables [55]. Unlike classical least squares regression, SEM assumes that variables are measured with errors but corrects them to produce unbiased estimates [58]. The modelling approach is also reliable at the preparatory, actual, and post-estimation stages [59]

and the results can be presented via a path diagram which makes the interpretation easier [60]. Nevertheless, when using MLE, the model's assumption of no symmetric missing data, non-linearity between predictor variables, and a large sample must be fulfilled [61].

When applying MLE in SEM we assumed that a 5-Likert scale used to measure the dependent variable is a sufficiently large scale to be treated as continuous [62]. Moreover, [62] argues that the drawbacks of applying Likert scale data as categorical lies in its specificity in reference to indicators of latent constructs, which is usually crude in nature and the crudeness arises from cutting the continuous scale of the theoretical construct into a set of ordered categories and imperfections of the scaling technique that lacks equally spaced intervals. Studies such as [63]; and Gazeloglu & Greenacre (2020) compared the application of MLE with other techniques such as Mean- and Variance-adjusted Weighted Least Square (WLSMV) in the analysis of Likert data and found that both yield comparable parameter estimates. However, a sample size above 2000 observations is recommended for WLSMV method. In addition, WLSMV procedure handles missing data using pairwise deletion which results in a covariance matrix that is not positive definite due to different subsets of cases used [57]. MLE is the natural choice when SEM is integrated with other techniques such as mixture modelling and handling missing data through robust model simulations [64]. MLE is also less prone to violations of Gauss-Markov's assumptions of least squares regression [65,51].

For moderation analysis, following [52,66]; and [67]; among others, we apply hierarchical regression to explain the interaction effect of SIN on the relationship between attitudes, subjective norm, and PBC and adoption intentions. To reduce multicollinearity, mean-centering and standardization of the predictor variables is usually conducted. While standardization is achieved by subtracting the mean value from data points and dividing them by the standard deviation, mean-centering is done by subtracting the mean of each variable from its original values [68]. When fitting the hierarchical regression model the following steps are followed: 1) standardize and mean-center all variables to make the interpretation easier, 2) ensure that the focal predictor and moderating variables are significant before fitting them together in the model, 3) include the interaction term and check whether it is significant. If the interaction term is significant but the focal predictor and the moderator variables are no longer significant, moderation is complete, but if the two also remain significant, there is partial moderation. Significant interaction terms can further be investigated to assess the nature of moderating effects using margin's plots at various levels of the focal predictor and the moderator variables e.g. at the mean (average), one standard deviation below the mean (low) and one standard deviation above the mean (high).

For mediation analysis, a classical [69] procedure was also verified as follows: 1) before mediation, we checked for a significant effect in path c, between SIN and intention; and 2) after mediation, there was also a significant effect in the path a, between SIN and mediators (attitude, subjective norm, and PBC), and path b, between the mediators and intention, then 3), path c', between SIN variables and intention should be insignificant or show a reduction in the significance for full (complete) and partial mediation, respectively. With full mediation, all the influence occurs through the mediating variable, and the coefficient of the direct effect becomes insignificant. For this study, if full mediation occurs, then SIN variables can be considered just as background factors/antecedents of the TPB constructs but with partial mediation, the variables are considered an extension of the TPB model.

3.4.2. Survey questions, Confirmatory Factor Analysis, and Reliability of scale

Table 1 shows the measures in the questionnaire. According to Ajzen's principle of compatibility discussed in [11,34]; and [70] any behavior should be defined by four elements: Target, Action, Context, and Time, sometimes referred to as the TACT principle. We followed this principle to ensure that all the TPB constructs and intentions are measured at the same level of generality or specificity and therefore compatible with actual adoption behavior for DRR measures. In this study, every question in the TPB framework was defined by keywords as follows: adopting/having (action) diversion channels or trees on my land (target) in the next rainy/planting season (time) to reduce landslide/flood disaster risks (context).

To ensure that SEM fits the data and data reliability, a Confirmatory Factor Analysis (CFA) was conducted to confirm adequate convergence of indicators to respective constructs [71]. As shown in Table 1, the recommended CFA loading of individual items per construct is ≥ 0.5 ($P < 0.01$) [71,18], except for PBC4. Nevertheless, the indicator was kept since dropping it would affect Cronbach's alpha and the average loading for the construct was still above 0.5. To confirm the reliability of the constructs, usually associated with the internal consistency of indicators per construct, we estimated the Cronbach's alpha proposed by [72,73]; and frequently applied in several studies such as [66,52]. The lowest alpha value of 0.71 was obtained which indicates reliability of the scales.

3.4.3. Fit indices for the CFA and structural equation models

In both the CFA and structural equation models we scaled the latent constructs by fixing one-factor variance to 1.00 (see [71,55]) but the initial stage of the CFA model revealed poor fit indices. Therefore, we looked at modification indices and added/removed some covariance terms to improve the fit. Usually, this is done if the index is significant at 0.05 with a chi-square value above 3.84 (Borges and Oude, 2016). Consequently, the major goodness of fit indices⁵, such as the ratio of the chi-square value to the degrees of freedom (χ^2/df), the Root Mean Square Error of Approximation (RMSEA), the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), and Pclose match the thresholds recommended in [71,55]. The results of the CFA and structural models in Table 2 show the data are adequately fitting the SEM for both the CFA and structural models. The fitness indices in the CFA model are the same across landslides and flood models with a marginal difference in Pclose. Though, for the structural models, SEM fits the data slightly better in terms of χ^2/df , RMSEA, and Pclose in the flood model.

⁵ As already indicated in this study, subjective norm and income were reported to have missing values and we applied Maximum Likelihood with missing values' command in Stata which does not report Standardized Root Mean Squared Residual (SRMR) values [61].

Table 1
Survey items, CFA loadings, and Cronbach's alpha

TPB survey questions (Adoption in this study implies digging diversion channels or planting trees by the household as DRR measures the next rainy/planting season)	Indicator	Landslide		Flood	
		Loading (>0.5)	Alpha (>0.7)	Loading (>0.5)	Alpha (>0.7)
Attitudes			0.90		0.92
I think having diversion channels or trees on my land next season to reduce LS/FL is good/bad	ATT1	0.82***		0.87***	
I think having diversion channels or trees on my land next season to reduce LS/FL is beneficial /harmful	ATT2	0.86***		0.87***	
I think having diversion channels or trees on my land next season to reduce LS/FL is wise/foolish	ATT3	0.87***		0.88***	
I think having diversion channels or trees on my land next season to reduce LS/FL is pleasant/unpleasant	ATT4	0.79***		0.84***	
I think having diversion channels or trees on my land next season to reduce LS/FL is valuable/not valuable	ATT5	0.71***			
Subjective Norm			0.79		0.79
People important to me want me to apply diversion channels or trees on my land next season to reduce LS/FL	SN1	0.74***		0.68***	
What others think when it comes to applying diversion channels or trees on my land next season to reduce LS/FL is (not) important to me	SN2	0.58***		0.60***	
I would be happy if people important to me to apply diversion channels or trees on their land next season to reduce LS/FL	SN3	0.75***		0.65***	
I always encourage other people important to me to apply diversion channels or trees on their land next season to reduce LS/FL	SN4	0.62***		0.68***	
Important others expect me to teach them how to apply diversion channels or trees on their land next season to reduce LS/FL	SN5	0.62***		0.64***	
It worries me when people important to me are severely hit by floods, thus I encourage them to apply div. channels or trees next season.	SN6			0.63***	
Perceived Behavioral Control			0.71		0.72
I can easily apply diversion channels or trees on my land next season to reduce LS/FL	PBC1	0.66***		0.63***	
I can easily train others on how to apply diversion channels or trees on their land next season to reduce LS/FL	PBC2	0.62***		0.66***	
I think of myself as someone who can apply diversion channels or trees on my land next season to reduce LS/FL	PBC3	0.75***		0.71***	
Only conditions beyond my control can stop me from applying diversion channels or trees on my land next season to reduce LS/FL	PBC4			0.48***	
Adoption intention			0.84		0.87
I intend to apply diversion channels or trees on my land next season to reduce LS/FL	INT1	0.76***		0.84***	
I wish to apply diversion channels or trees on my land next season to reduce LS/FL	INT2	0.83***		0.80***	
I will apply diversion channels or trees on my land next season to reduce LS/FL	INT3	0.73***		0.78***	
I plan to apply diversion channels or trees on my land next season to reduce LS/FL	INT4	0.68***		0.73***	
Actual adoption					
I have already applied diversion channels or trees on my land to reduce LS/FL	AB1				
Social Information Network Questions					
Kinship (Binary: relative or not)					
How is neighbor X related to you?					
How is neighbor Y related to you?					
How is neighbor Z related to you?					
How is Village member X related to you?					
How is the village chairperson related to you?					
How is the village general secretary related to you?					
Technical info (Binary: yes or no)					
Did you share any technical info with an extension worker in the last 6 months?					
Did you share any technical info with an NGO officer in the last 6 months?					
Did you share any technical info with a farmer organization leader in the last 6 months?					
Sharing DRR info (continuous)					
How many times do you talk to village member X about DRR in a month?					
How many times do you talk to neighbor X about DRR in a month?					
How many times do you talk to the village chairperson about DRR in a month?					
How many times do you talk to the village secretary about DRR in a month?					

Note: n=602, ***P <.01 for item loadings. All TPB questions were based on a Likert scale (1–5): strongly disagree to strongly agree. Acronyms; ATT: Attitude, SN: Subjective norm, PBC: Perceived Behavioral Control, INT: Intention, AB: Actual Behavior, LS: Landslides, FL: Floods. The number in parentheses in the headings represents thresholds; CFA Loadings, and Cronbach's alpha for actual adoption and SIN variables are not estimated because they were assessed as observed variables and the averages used.

4. Results

4.1. Descriptive statistics

Household-specific information in Table 3 indicates that about 67% of the households were selected from the Rwenzori sub-region

Table 2
Model fit indices for the CFA and structural equation models

Fit index	Recommended threshold	CFA (Landslide)	CFA (Flood)	CFA (Combined)	Structural (landslide)	Structural (flood)	Structural (combined)
χ^2/df	<3.00	2.33	2.42	2.53	2.19	2.12	2.73
RMSEA	<0.08	0.05	0.05	0.05	0.05	0.04	0.05
CFI	≥0.90	0.98	0.98	0.95	0.98	0.98	0.94
TLI	≥0.90	0.97	0.97	0.94	0.97	0.97	0.93
Pclose	>0.05	0.72	0.59	0.41	0.87	0.92	0.04

and 33% from Ankole. About 87% of the household heads were male and 68% of them had only a primary education level or lower. The average age of the household head was about 48 years old, and a household consisted, on average of six members. A household earns on average 1,750,000 UGX per year and owns about four acres of land. Also, about 72% of the households indicate that farming is the main livelihood source. In terms of altitude, homesteads were located at about 1300m above sea level.

Table 4 shows that on average, each household obtained technical information (Technical info) from at least one of the members in the professional network, six months before the study, shared DRR-related information (Sharing DRR informal) three times per month with a member in the informal network and had at least two relatives among the six selected informal network members (Kinship). For the 5-Likert scale questions per set of items in the TPB constructs, an average 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 predicted variables (intention and actual adoption), and SIN and TPB predictors, except for the association between Sharing DRR informal, and Technical info and actual adoption (landslide model). Attitude and subjective norm are - as in many studies- correlated [70] but adding other explanatory variables, in this case, PBC, SIN, and covariates in the regression model, often reduces the problem and gives reliable estimates.

4.2. TPB determinants of intention and actual adoption behavior

From the FGDs we learned that awareness, attitude, subjective norm, and PBC are the main drivers of adoption behavior, among other factors. In Fig. 3(a) and 3(b), SEM results further offered support for the efficacy of the TPB framework for the adoption of DRR measures. All the three TPB constructs positively and significantly influence adoption intention in both the landslide and flood models. PBC had the strongest influence (landslide: $\beta = 0.85$, $p < 0.01$ and Flood: $\beta = 0.66$, $p < 0.01$), followed by subjective norm (landslide: $\beta = 0.28$, $p < 0.01$ and Flood: $\beta = 0.35$, $p < 0.01$), and attitude (landslide: $\beta = 0.12$, $p < 0.05$ and Flood: $\beta = 0.12$, $p < 0.01$). The three constructs account for 85% and 58% of the total variations in intention to control landslides and floods, respectively. Moreover, intentions significantly influence actual adoption (landslide: $\beta = 0.34$, $p < 0.10$, and Flood: $\beta = 0.12$, $p < 0.10$). Only 5% of the actual adoption behavior (landslide) and 7% (flood model) is predicted by intention. This suggests an intention-behavior gap where a bigger portion of the variation in actual adoption is not explained by the TPB models. Regressing PBC directly on behavior did not give meaningful results, suggesting no difference in volitional control among respondents over adoption behavior for DRR measures.

4.3. Interrelation between adoption behavior to control landslides and floods

Further, Fig. 3(c) above shows a positive and significant correlation (via covariance terms) in intention (coefficient 0.44, $p < 0.01$), and actual adoption (coefficient 0.60, $p < 0.01$) between landslide and flood models. This is because the same location is often simultaneously affected by the two disasters. This indicates that if someone plans to apply (or has adopted) DRR measures to reduce landslides he/she is also likely to express similar behavior towards flood control (or vice versa), indicating a multi-hazard response.

4.4. Effect of SIN on adoption intention

4.4.1. Moderation analysis

This study further analyzed whether SIN variables moderate the relationship between attitude, subjective norm, and PBC and adoption intention. Hierarchical regression model results in Table 5 show that in the first model, attitude, subjective norm and PBC are significantly related with adoption intention and explain about 56% and 57% of the variation in the landslide and flood models, respectively. In the second model the coefficients of all the SIN variables were significant and therefore included as interaction effects (with attitude, subjective norm and PBC) in the third model. This significantly enhanced the model's predictive power based on R^2 (landslide: 58% and floods: 61%). Of the three theoretical predictors of intention, the impact of attitude on intention is influenced more by SIN in the landslide model, while in the flood's model both attitude and PBC are influenced by SIN. Among the SIN variables, sharing Technical info within the professional network is the main moderator of behavioral intentions in the floods model, while in the landslide model both sharing Technical info and Sharing DRR informal moderate the relation between attitude and intentions. Lastly, for all the significant interactions, the main effects also remained significant suggesting partial moderation, except for attitude when moderated by Technical info (flood model) which demonstrates complete moderation.

In the landslide model, the interaction between Technical info and attitude as well as Sharing DRR informal and attitude showed an enhancing effect on adoption intentions. The corresponding margin's plots (appendix A) shows that at low (negative) attitude, adoption intention is low for all the respondents with low, average, and high access to technical information and sharing DRR information in the informal networks. As attitude becomes positive and the farmer accesses more information, intentions to apply DRR measures increase compared to those with positive attitude but low access to information. Surprisingly, Technical info played an antagonistic role in which increasing access to technical information negatively affected the relationship between PBC and intention.

Table 3
Household-specific information

Categorical Variables	Statistic (%)
Gender (Household Head)	
Male	524 (87.04%)
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's region	
Rwenzori	402 (66.78%)
Ankole	200 (33.22%)
Continuous variables	Mean
Age of the household head (years)	47.69
Family size (members)	6.14
Land owned (acres)	3.88
Household annual income (UGX)	1,753,010
Location altitude (meters)	1317.20

Note. N=602

Table 4
Descriptive statistics and correlation coefficients

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

Notes. N=602. Significance levels: ***p < .01, **P < 0.05, *P < 0.1; The mean and Standard Deviation (SD) for Sharing DRR informal, Technical info, and Kinship are similar across the flood and landslide models because the questions were not examined separately. Acronyms: PBC: Perceived Behavioral Control, Subj norm: subjective norm, Sharing DRR informal: sharing information on disaster reduction in the informal network and Technical info: sharing technical information from the professional networks.

We probed this further using the margin's plot, which indicates that at low PBC, households with more access to Technical info express higher intention to apply DRR measures, which is quite intuitive. The intention increases with increasing PBC for all categories, but surprisingly increases faster for those with less access to Technical info. In the flood model, Technical info has a significantly positive moderating effect on the relationship between attitude and intentions and a negative effect on the relationship between subjective norm and adoption intentions, suggesting that information reduces adoption behavior based on social pressure (subjective adoption decisions).

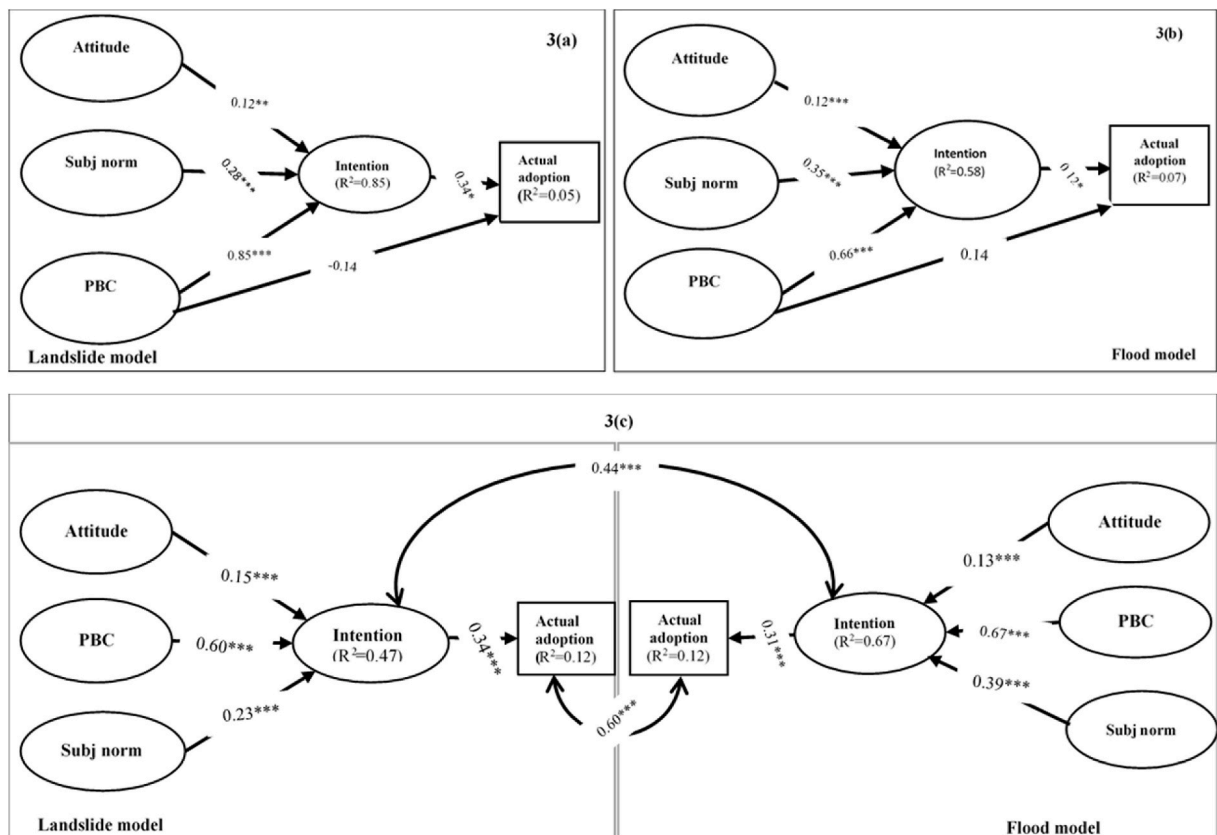


Fig. 3. The TPB model results: TPB determinants of intention and actual adoption behavior shown by 3(a) & 3(b); Interrelations between adoption behavior for landslides and floods in 3(c). Notes. PBC: Perceived Behavioral Control, Subj norm: subjective norm. The standardized coefficients are presented. Coefficients of the control variables are not shown to improve the figure readability since they are not of direct interest in this study; N=602.

Table 5

Results of hierarchical regression analysis for the moderation effect

Variable	Landslide model			Flood model		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
TPB Constructs						
Attitude	0.115**	0.111**	-0.292**	0.116**	0.093*	-0.144
SN	0.317***	0.329***	0.457***	0.377***	0.420***	0.763***
PBC	0.501***	0.496***	0.614***	0.536***	0.521***	0.437***
SIN variables						
Sharing DRR info		-0.021**	-0.092		-0.037***	0.005
Technical info		0.061***	-0.206		0.117***	0.271
Kinship		0.038***	-0.062		0.036***	-0.148
Interaction effects						
Attitude × Sharing DRR info			0.136***			0.036
Attitude × Technical info			0.115**			0.112**
Attitude × Kinship			0.068			0.053
PBC × Sharing DRR info			-0.044			0.008
PBC × Technical info			-0.079*			0.012
PBC × Kinship			0.022			0.051
SN × Sharing DRR info			-0.058			-0.073
SN × Technical info			0.017			-0.165***
SN × Kinship			-0.053			-0.026
R ²	0.556	0.569	0.583	0.5686	0.592	0.607
Δ in R ²		0.012	0.014		0.023	0.015
F-statistic	250.570***	5.860***	2.230**	262.770***	11.620***	2.48**

Notes: Acronyms. SN: subjective norm, PBC: perceived behavioral control, Technical info: Technical information from the professional networks, Sharing DRR informal: Sharing Disaster Risk Reduction (DRR) information among the informal networks. Significance level. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$. All variables were standardized and mean-centered; N=602

4.4.2. Mediation analysis

Lastly, through mediation analysis, we investigated how SIN variables act as background factors to influence the beliefs that give rise to TPB constructs (attitude, subjective norm and PBC). Before mediation, all the direct relationships between SIN and intention were significant, except Sharing DRR informal (flood model), which was therefore excluded from the analysis. In Fig. 4 for the landslide model, the relationship between Sharing DRR informal and adoption intention is fully (completely⁶) mediated by subjective norm and attitude. Also, the relationship between Technical info and intention is completely mediated by PBC. Therefore, Sharing DRR information in the informal social networks (Sharing DRR informal) acts as a background factor influencing beliefs that give rise to attitude and subjective norm as does sharing Technical info within professional networks which influences beliefs that give rise to PBC. Furthermore, partial mediation is observed between Kinship and intention through attitude (the coefficient in path c: $\beta = 0.122$; $p < 0.01$ reduces to c': $\beta = 0.035$ $p < 0.01$), Kinship and intention through subjective norm (c: $\beta = 0.122$; $p < 0.01$ to c': $\beta = 0.032$; $p < 0.01$), Sharing DRR informal and intention through PBC (c: $\beta = 0.130$; $p < 0.01$ to c': $\beta = -0.023$; $p < 0.10$), Technical info and intention through subjective norm (c: $\beta = 0.086$; $p < 0.10$ to c': $\beta = 0.053$; $p < 0.05$). In the Flood model, only the paths from Technical info to intention through PBC (c: $\beta = 0.144$; $p < 0.01$ to c': $\beta = 0.069$; $p < 0.10$) and from Kinship to intention through subjective norm (c: $\beta = 0.095$; $p < 0.05$ to c': $\beta = 0.034$; $p < 0.05$) demonstrated partial mediation.

5. Discussions, limitations, and conclusions

5.1. Discussion and implications

5.1.1. TPB determinants of intention and actual adoption behavior

The Theory of Planned Behavior (TPB) has been widely applied in health sciences, social media, crime, and social justice studies in western cultures [74,75,6,16,76] but has scarcely focused on the adoption of farm-level DRR measures in developing countries. By explaining up to 85% of variations in the intentions, this study demonstrated that TPB can also predict farmers' adoption of DRR measures in the Rwenzori and Ankole in Western Uganda, two sub-regions that are typical of a disaster-prone rural setting in a developing country. PBC is the main predictor of intention and this is consistent with other studies [77,6,13]. It emphasizes that gaining control over behavior is a major step towards sustainable environmental management. Policy-making should focus on effective and regular training to increase farmers' adoption of DRR measures amidst the escalating problems of climate change. They should also ensure participatory needs assessment, designing, and implementation of DRR programs that tackle barriers to farmers' volitional control.

Perceived control over 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, as revealed by the FGDs, farmers in the study area lack adequate knowledge due to limited access to information targeted to DRR, which was also explained by [42]. The significant impact of subjective norm on adoption intention is quite intuitive given the nature of rural settings in developing countries with a strong social networks [6]. Household interdependence is not only manifested in sharing tools, social labor, food, shelter, and seed but also learning by observing others' practices. The influence of attitude on adoption intentions is also positive and significant, suggesting that farmers who view the outcome of adoption more favorably are likely to show intention to apply it. Attitude being comparatively less significant is in line with a study by [78] which argued that farmers' attitudes are less important compared to perceived ability and social pressures. However, the result highlights the need to examine the underlying critical factors that promote positive attitudes toward adoption when designing policy measures.

Both descriptive statistics and SEM revealed higher intention than actual adoption indicating an intention-behavior gap. This is also discussed in other studies such as [15,16,17] and [76]. For this study, the gap could be explained by limited technical ability, lack of trust in the measures to control stronger landslides and floods, and shortage of supplies for DRR measures in cash-strapped rural settings [54,79]. Strategic policy interventions should target such constraints by, for example, promoting rural finance schemes and tree nurseries. As revealed in the FGD, stronger frequent floods associated with major rivers in the area like Nyamwamba, and Humya, frustrate smallholders' adaptive efforts. Therefore, capital- and technical-intensive measures such as protecting riparian forest buffer zones, maintaining river channels through dredging, building stronger and broader bridges, and enforcing proper land use practices should be implemented by the government [80,81].

5.1.2. Interrelation between adoption behavior to control landslides and floods

Households in the study area are at risk of multiple interacting disasters (e.g., landslides and floods) that generate synergies. The multi-hazard impact of landslides and floods can be explained by the spatial, cascading temporal relationship. Sometimes landslide debris blocks the natural water channels forming temporary dams that break and the water is released at once hence overflowing the channel [3] which results in flooding. Such spatial and temporal relations trigger an interrelation in the adoption behavior, as revealed by this study, where both the intention and actual adoption of DRR measures against landslides and floods are highly correlated.

Based on the focus group discussions, most farmers buy small land parcels in lowland areas perceived as less risky to disasters to establish homesteads but use plots on steep slopes for farming. They also choose lowland areas for settlements because the highland is under-supplied with transport and communication systems, water, education, and health facilities. Therefore, when they (plan to)

⁶ Complete mediation is when the significance of a 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 of the path between the predictor and outcome reduces after mediation, suggesting part of the effect goes through the indirect path; no mediation means none of the two types of mediation is reflected.

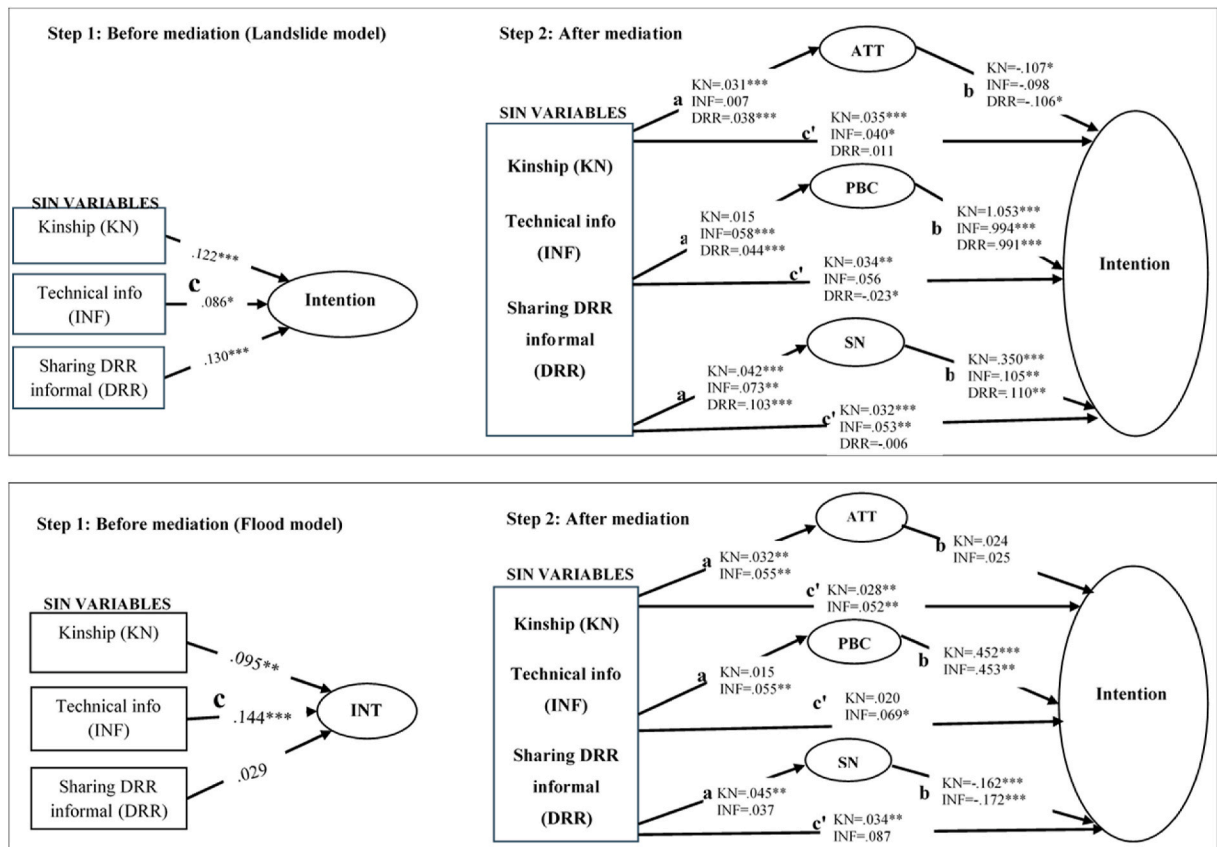


Fig. 4. Mediation analysis. Acronyms; PBC: Perceived Behavioral Control, ATT: attitude, SN: subjective norm, DRR: Sharing Disaster Risk Reduction information in the informal networks (also Sharing DRR informal), SIN: Social Information Network, KN: Kinship, INF: Technical information with the professional network (also Technical info). Significance levels: *** $p < .01$, ** $p < 0.05$, * $p < 0.1$. Sharing DRR informal (flood model) did not pass BK's first step mediation criteria and was excluded from the mediation analysis; $N=602$.

apply measures to protect their plots on highlands against landslides, they also want to keep their homesteads (and a few crops around) safe from floods resulting from massive movements of water and the debris from upslope. The results could also be explained by the fact that farmers who (intend to) adopt a measure for one disaster are likely to be those with control over the adoption behavior in general in terms of resources and skills or have more positive attitudes and subjective norms which are associated with intention. The findings inform policy-makers to consider such interrelations at each stage of planning and resource allocation and not to underestimate spatially related disasters, which also agrees with [48]. The result also suggests the need for interventions that provide comprehensive training on multiple hazards.

5.1.3. Effect of SIN on adoption intentions

This study further investigated whether the farmer's SIN, as background variables moderate the relationship between the TPB constructs or influences adoption intentions indirectly through attitude, PBC, and subjective norm. Moderation analysis revealed that, among the theoretical determinants of intention, attitude towards adoption of DRR measures is moderated more by SIN variables, especially by sharing Technical info within professional networks. It is reasonable that one's attitude significantly improves when they access more information shared by professional or informal networks. Indeed, several studies (e.g. [52]) have observed lags in adoption of agricultural technologies due to poor attitudes when there is limited access to information. Information triggers positive evaluation of a measure by enhancing the knowledge about effective measures and methods of application and sharing success stories about DRR measures. Attitudes towards adoption of DRR measures, when moderated by sharing DRR information in the informal networks (Sharing DRR informal) was only significant for the landslide model, which could be explained by the idiosyncratic nature of shallow, less reported landslides (see [54]). Landslides have more localized impacts compared to floods, thus stimulating information sharing within the immediate local networks. Moreover, this study showed that sharing Technical info within professional networks negatively moderated the relationship between subjective norm and intention suggesting that, with technical advice, adoption behavior based on social pressures (usually associated with less planning) reduces.

Beyond additive modeling conducted by moderation analysis, and in line with the recommendation by [35]; we explored the mediating mechanism of TPB cognitions on SIN as background variables. This study revealed that sharing DRR information in the informal networks (Sharing DRR informal) is affecting attitudes, social norms and PBC in the landslide more than flood model. This can

be attributed to the fact that landslides are idiosyncratic shocks with localized impact and therefore information sharing within informal (and hence often local) networks becomes more relevant. Our study further reveals that sharing DRR information within informal networks does not influence intention directly but only through one's attitudes and subjective norms as does sharing Technical info within professional networks by influencing intentions only through PBC. Overall, many SIN variables significantly influence the TPB constructs, which suggests that both professional and informal networks should be complementary, in that informal networks cannot substitute formal trainings because members in the network tend to possess identical ideas and lack technical grasp of innovations [6]; Muange et al., 2014). There is need to promote both networks because not all farmers attend formal training or can share the information effectively. Technical non-redundant information received by a few can further be transferred using informal networks [82].

Mediation analysis confirms the preposition that next to the TPB constructs, other factors also affect intentions either directly or because they are mediated by the TPB constructs [14]. The results show that the stronger the network ties (kinship) the higher adoption intentions and the higher the subjective norm and attitudes. The latter construct (attitude) and PBC also mediate the effect of sharing DRR information in the informal networks on intention in the landslide model. Most land-use decisions and access to supplies such as tools and tree seedlings in developing countries depend on family ties and social links [25]. Therefore, policy interventions should focus on how to exploit social links, for example, through establishing disaster sensitization groups and disaster rescue teams which positively influence farmers' attitudes and perceived control over the adoption behavior.

Among the TPB constructs, attitude was the least significant predictor of intention and both moderation and mediation analysis revealed that the construct is significantly influenced by sharing DRR information in informal networks (Sharing DRR informal). This suggests that targeted information is one of the critical factors that promotes positive attitudes towards adoption. Additionally, as revealed by the classical TPB model, PBC is the most significant predictor of intentions and sharing Technical info from professional networks had overall higher direct effect on intention to adopt flood control measures before mediation. Also, the moderation effect of Technical info on the relationship between PBC and intention under landslide model revealed higher intention with higher access to technical information even when the respondent expressed low PBC, which seems to suggest that access to technical advice positively and significantly influences one's adoption plans even with less control over the adoption process. Moreover, mediation analysis revealed that Technical info was fully mediated by PBC (landslide model), which means that PBC has its origin in the technical information, suggesting the indispensable role played by the professional networks.

5.2. Limitations of the study

While the study posits several theoretical and practical strengths, four main weaknesses are highlighted. First, the study analyzed cross-section data to assess the association between TPB determinants of adoption behavior and examined the effect of SIN as background variables, but such a design is limited in testing the causal-effect relationships [13]. Further research should explore this using longitudinal designs. Second, random matching within the sample approach was applied, involving nine members from a random sample to collect data on SIN. The method can be costly when dealing with large sample sizes (Muange et al., 2015) and presents unequal access to key networks based on gender, vulnerable groups, and other social links that span out geographically. Further studies should apply theoretically appealing and cost-effective methods such as paired actors (dyads) where a respondent names their social links. Third, though this study was quantitative, we collected qualitative data using FGDs to inform questionnaire development and provide insights to better understand and contextualize the results of the quantitative analysis. Further studies could design relevant codes into emergent themes and use constant comparison analysis for the narratives from the FGDs [46]. Fourth, there was also a limitation in not identifying sociodemographic factors of the people (in the random match) used to investigate SIN.

5.3. Conclusions

This study investigated the role of Social Information Networks (SIN) in explaining farmers' adoption behavior against landslides and floods from a TPB perspective. The study revealed that PBC is the main predictor of intention, followed by subjective norm and attitude, though adoption intention was lower than actual adoption, revealing an intention-behavior gap. The correlation in adoption of measures to control landslides and flood further revealed the need to design policies that tackle both risks simultaneously. Moreover, farmer's SIN matters a lot in explaining adoption intentions. They moderate the relation between the TPB constructs and intention, but the effect is not merely additive. The SIN variables also influence the informational beliefs that give rise to the TPB constructs. For landslides that are characterized by localized shocks, informal networks are key in moderating attitudes towards landslide control and the adoption intention is driven more by attitudes if more information is shared in informal networks. Sharing technical information also moderates the relation between the TPB constructs and adoption intention, but also affects the beliefs that give rise to the TPB constructs. This points towards the immense need for regular training by professional networks to increase adoption intentions. Therefore, both professional and informal networks play a significant role in determining intention which further suggests that the role of extension services cannot be substituted by informal social networks and vice versa, but that the two are complementary. The findings provide strategic policy lessons and pave way for further research on how professional and informal networks can be synergized to improve access to technical and timely information to enhance farmers' adoption of DRR measures.

Statements and declarations

Funding

We appreciate VLIR-UOS - for funding the study through the TEAM project (UG2019TEA492A105): Digital citizen Science for community-based Resilience on Environmental Management (D-SIRE).

Author contributions

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

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

We appreciate VLIR-UOS - for funding the study through the TEAM project (UG2019TEA492A105): Digital citizen Science for community-based Resilience on Environmental Management (D-SiRE).

Appendix A Margin's plots of the interaction effect between SIN and TPB constructs in the moderation analysis

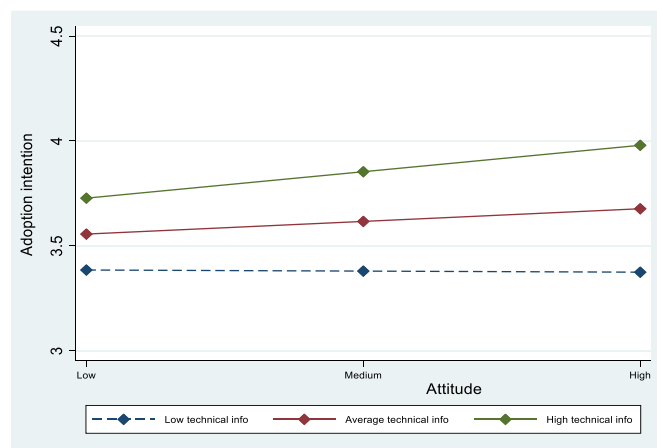


Fig. 5(a). Attitude and Technical information (Landslide model).

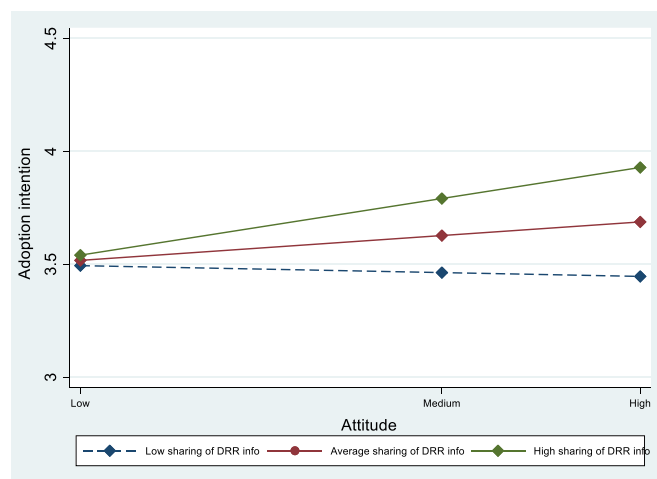


Fig. 5(b). Attitude and Sharing DRR info (Landslide model).

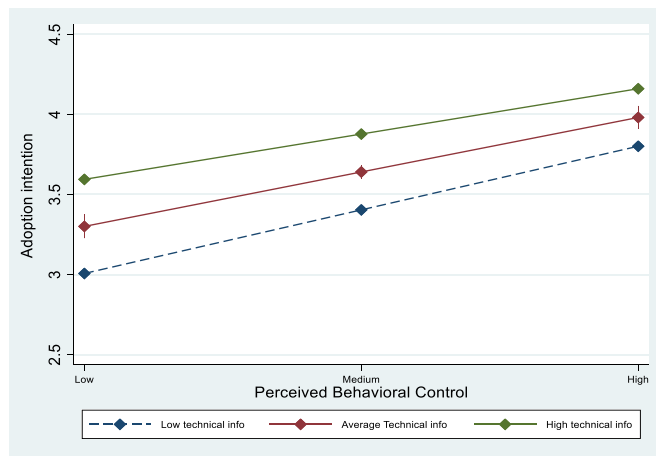


Fig. 5(c). BPC and Technical info (Landslide model).

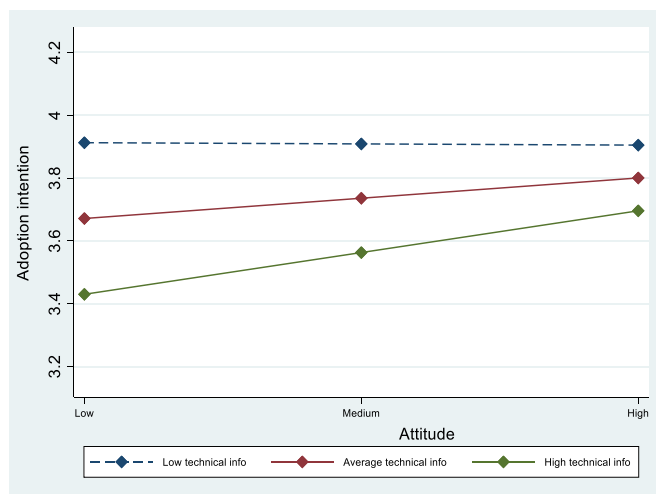


Fig. 5(d). Attitude and Technical info (Flood model).

Appendix A. Margin's plots for the hierarchical regression analysis for the moderation effect (Cont'd)

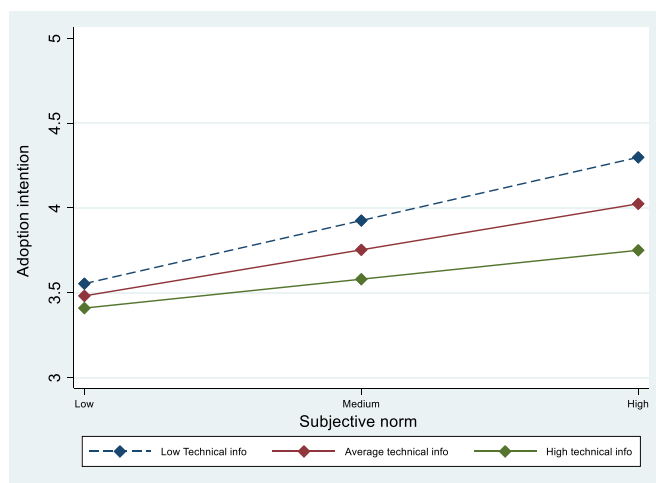


Fig. 5(e). Subjective norm and Technical info (Flood model).

References

- [1] L. Stavi, S. Prior, N. Thevs, Desertification, land use, and the transformation of global drylands, *Frontiers in Ecology and the Environment* 13 (1) (2022) 28–36, <https://doi.org/10.1890/140162>.
- [2] E. Cavallo, O. Becerra, L. Acevedo, *The Impact of Natural Disasters on Economic Growth*, Issue October, IDB Working Paper Series 83 (2021).
- [3] L. Jacobs, J. Maes, K. Mertens, J. Sekajugo, W. Thiery, N. van Lipzig, J. Poesen, M. Kervyn, O. Dewitte, Reconstruction of a flash flood event through a multi-hazard approach: focus on the Rwenzori Mountains, Uganda, *Natural Hazards* 84 (2) (2016) 851–876, <https://doi.org/10.1007/s11069-016-2458-y>.
- [4] D. Alexander, G. Pescaroli, What are cascading disasters? *UCL Open Environment* 1 (1) (2019) 1–6, <https://doi.org/10.14324/111.444/ucloe.000003>.
- [5] UN (United Nations), *Population Division (2019 Revision)*, 2019. [OurWorldInData.org/world-population-growth/](https://www.worldpopulationgrowth.org/) • CC BY%0AS.
- [6] F. Caffaro, M. Roccato, M. Micheletti Cremasco, E. Cavallo, An ergonomic approach to sustainable development: The role of information environment and social-psychological variables in the adoption of agri-environmental innovations, *Sustainable Development* 27 (6) (2019) 1049–1062, <https://doi.org/10.1002/sd.1956>.
- [7] L. Jacobs, C. Kabaseke, B. Bwambale, R. Katutu, O. Dewitte, K. Mertens, J. Maes, M. Kervyn, The geo-observer network: A proof of concept on participatory sensing of disasters in a remote setting, *Science of the Total Environment* 670 (2019) 245–261, <https://doi.org/10.1016/j.scitotenv.2019.03.177>.
- [8] J. Maes, K. Mertens, L. Jacobs, B. Bwambale, L. Vranken, O. Dewitte, J. Poesen, M. Kervyn, Social multi-criteria evaluation to identify appropriate disaster risk reduction measures: application to landslides in the Rwenzori Mountains, Uganda, November 2017, *Landslides* 2017, <https://doi.org/10.1007/s10346-018-1030-0>.
- [9] A. Kumawat, D. Yadav, K. Samadharmam, R. Ittyamkandath, Soil and Water Conservation Measures for Agricultural Sustainability, *Intech I* (2020) 13, <https://doi.org/10.5772/intechopen.92895> (Issue tourism).
- [10] D.N. Mubiru, M. Radeny, F.B. Kyazze, A. Zziwa, J. Lwasa, J. Kinyangi, C. Mungai, Climate trends, risks and coping strategies in smallholder farming systems in Uganda, *Climate Risk Management* 22 (2018) 4–21, <https://doi.org/10.1016/j.crm.2018.08.004>.
- [11] I. Ajzen, M. Fishbein, *Predicting Changing Behavior*, Taylor & Francis Group, 2010.
- [12] I. Anwar, I. Saleem, K.M.B. Islam, P. Thoudam, R. Khan, Entrepreneurial intention among female university students: Examining the moderating role of entrepreneurial education, *Journal for International Business and Entrepreneurship Development* 12 (4) (2020) 217–234, <https://doi.org/10.1504/JIBED.2020.110254>.
- [13] A.K. Das, M.M. Abdul Kader Jilani, M.S. Uddin, M.A. Uddin, A.K. Ghosh, Fighting ahead: Adoption of social distancing in COVID-19 outbreak through the lens of theory of planned behavior, *Journal of Human Behavior in the Social Environment* 31 (1–4) (2021) 373–393, <https://doi.org/10.1080/10911359.2020.1833804>.
- [14] M. Fishbein, I. Ajzen, *Belief, Attitude, Intention and Behaviour*, 1260, Addison Publishing Company, 1975, <https://doi.org/10.2174/1877945x11101010001>.
- [15] M.M. Al-Debei, E. Al-Lozi, A. Papazafeiropoulou, Why people keep coming back to Facebook: Explaining and predicting continuance participation from an extended theory of planned behaviour perspective, *Decision Support Systems* 55 (1) (2013) 43–54, <https://doi.org/10.1016/j.dss.2012.12.032>.
- [16] N. Pérez-Macías, J.L. Fernández-Fernández, A. Rúa Vieites, The impact of network ties, shared languages and shared visions on entrepreneurial intentions of online university students, *Studies in Higher Education* 45 (12) (2020) 2526–2540, <https://doi.org/10.1080/03075079.2019.1619682>.
- [17] Q. Yang, S. Wu, How Social Media Exposure to Health Information Influences Chinese people's Health Protective Behavior during Air Pollution: A Theory of Planned Behavior Perspective, *Health Communication* 36 (3) (2021) 324–333, <https://doi.org/10.1080/10410236.2019.1692486>.
- [18] R. Kabbiri, M. Dora, V. Kumar, G. Elepu, X. Gellynck, Mobile phone adoption in agri-food sector: Are farmers in Sub-Saharan Africa connected? *Technological Forecasting & Social Change* (2017) <https://doi.org/10.1016/j.techfore.2017.12.010>. October, 0–1.
- [19] H.D. Shannon, R.P. Motha, Managing weather and climate risks to agriculture in North America, Central America and the Caribbean, *Weather and Climate Extremes* 10 (2015) 50–56, <https://doi.org/10.1016/j.wace.2015.10.006>.
- [20] E.M. Rogers, *Diffusion of innovations*, Free press, New York, USA, 2003.
- [21] UNISDR (United Nations International Strategy for Disaster Reduction), Sendai Framework for Disaster Risk Reduction 2015 - 2030, UN 37 (2015). Issue 2.
- [22] K. Vasilaky, K.L. Leonard, As Good as the Networks They Keep?: Improving Farmers' Social Networks via randomized Information exchange in Rural Uganda, *Economic Development and Cultural Change* 66 (4) (2016).
- [23] M. Abid, G. Ngariyui, J. Scheffran, F. Zulfiqar, The Role of Social Networks in Agricultural adaptation to Climate Change: implications for Sustainable Agriculture in Pakistan, *Climate* 1–21 (2017), <https://doi.org/10.3390/cli5040085>.
- [24] A. Pratiwi, A. Suzuki, Effects of farmers' social networks on knowledge acquisition: lessons from agricultural training in rural Indonesia, *Journal of Economic Structures* 6 (1) (2017), <https://doi.org/10.1186/s40008-017-0069-8>.
- [25] A. Ramirez, The Influence of Social Networks on Agricultural technology Adoption, *Procedia - Social and Behavioral Sciences* 79 (2013) 101–116, <https://doi.org/10.1016/j.sbspro.2013.05.059>.
- [26] C. Murendo, M. Wollni, A.D. Brauw, N. Mugabi, Social Network Effects on mobile money Adoption in Uganda, *The Journal of Development Studies* (2018) 1–16, <https://doi.org/10.1080/00220388.2017.1296569>.
- [27] S. Bamberg, G. Möser, Twenty years after Hines, Hungerford, and Tomera: A new meta-analysis of psycho-social determinants of pro-environmental behaviour, *Journal of Environmental Psychology* 27 (1) (2007) 14–25, <https://doi.org/10.1016/j.jenvp.2006.12.002>.
- [28] I. Ajzen, J. Klobas, Fertility intentions, *Demographic Research* 29 (December) (2013) 203–232, <https://doi.org/10.4054/demres.2013.29.8>.
- [29] I. Ajzen, *The Theory of Planned Behavior*, *Organizational Behavior and Human Decision Processes* 50 (1991) 179–211.
- [30] C.J. Armitage, P. Norman, M. Conner, Can the Theory of Planned Behaviour mediate the effects of age, gender and multidimensional health locus of control? *British Journal of Health Psychology* 7 (3) (2002) 299–316, <https://doi.org/10.1348/135910702760213698>.
- [31] P. Andreev, T. Heart, H. Maoz, N. Pliskin, Validating Formative Partial Least Squares Models: methodological Review and Empirical illustration, *Thirtieth International Conference on Information Systems*, January (2009) 535–544.
- [32] T. Coltman, T.M. Devinney, D.F. Midgley, S. Venaik, Formative versus reflective measurement models: Two applications of formative measurement, *Journal of Business Research* 61 (12) (2008) 1250–1262, <https://doi.org/10.1016/j.jbusres.2008.01.013>.
- [33] E.A. Khan, M.N.A. Dewan, M.M.H. Chowdhury, Reflective or formative measurement model of sustainability factor? A three industry comparison, *Corporate Ownership and Control* 13 (2) (2016) 83–92, <https://doi.org/10.22495/cocv13i2p9>.
- [34] Jaap Sok, J.R. Borges, P. Schmidt, I. Ajzen, Farmer Behaviour as Reasoned Action: A Critical Review of Research with the Theory of Planned Behaviour, *Journal of Agricultural Economics* 72 (2) (2021) 388–412, <https://doi.org/10.1111/1477-9552.12408>.
- [35] K. Umeh, R. Patel, Theory of planned behaviour and ecstasy use: An analysis of moderator-interactions, *British Journal of Health Psychology* 9 (1) (2004) 25–38, <https://doi.org/10.1348/135910704322778704>.
- [36] J. Christian, C.J. Armitage, Attitudes and intentions of homeless people towards service provision in South Wales, *British Journal of Social Psychology* 41 (2) (2002) 219–231, <https://doi.org/10.1348/014466602760060101>.
- [37] R. Robinson, C. Smith, Psychosocial and demographic variables associated with consumer intention to purchase sustainably produced foods as defined by the midwest food alliance, *Journal of Nutrition Education and Behavior* 34 (6) (2002) 316–325, [https://doi.org/10.1016/S1499-4046\(06\)60114-0](https://doi.org/10.1016/S1499-4046(06)60114-0).
- [38] E.L. Tolma, B.M. Reininger, J. Ureda, A. Evans, Cognitive motivations associated with screening mammography in Cyprus, *Preventive Medicine* 36 (3) (2003) 363–373, [https://doi.org/10.1016/S0091-7435\(02\)00022-1](https://doi.org/10.1016/S0091-7435(02)00022-1).
- [39] I. Ajzen, The theory of planned behaviour: reactions and reflections, *Psychology and Health* 26 (9) (2011) 1113–1127, <https://doi.org/10.1080/08870446.2011.613995>.
- [40] B. Bwambale, K. Mertens, T. Kahigwa, International Journal of Disaster Risk Reduction The socio-epistemic process of indigenous disaster risk reduction: Evidence of adapting yet endangered indigenous strategies, *International Journal of Disaster Risk Reduction* 75 (April) (2022), 102953, <https://doi.org/10.1016/j.ijdrr.2022.102953>.

- [41] L. Jacobs, O. Dewitte, J. Poesen, J. Maes, K. Mertens, J. Sekajugo, M. Kervyn, Landslide characteristics and spatial distribution in the Rwenzori Mountains, Uganda, *Journal of African Earth Sciences* 134 (2017) 917–930, <https://doi.org/10.1016/j.jafrearsci.2016.05.013>.
- [42] K. Mertens, L. Jacobs, J. Maes, J. Poesen, M. Kervyn, L. Vranken, Disaster risk reduction among households exposed to landslide hazard: A crucial role for self-efficacy? *Land Use Policy* 75 (January) (2018) 77–91, <https://doi.org/10.1016/j.landusepol.2018.01.028>.
- [43] L. Jacobs, O. Dewitte, J. Poesen, D. Delvaux, W. Thiery, M. Kervyn, The Rwenzori Mountains, a landslide-prone region? *Landslides* 13 (3) (2015) 519–536, <https://doi.org/10.1007/s10346-015-0582-5>.
- [44] D. Nseka, V. Kakembo, Y. Bamutaze, F. Mugagga, Analysis of topographic parameters underpinning landslide occurrence in Kigezi highlands of southwestern Uganda, *Natural Hazards* 99 (2) (2019) 973–989, <https://doi.org/10.1007/s11069-019-03787-x>.
- [45] R.L. Breen, A Practical Guide to Focus-Group Research A Practical Guide to Focus-Group Research, *Journal of Geography in Higher Education* 30 (3) (2007) 463–475, <https://doi.org/10.1080/03098260600927575>.
- [46] A.J. Onwuegbuzie, W.B. Dickinson, N.L. Leech, A.G. Zoran, A Qualitative Framework for Collecting and Analyzing Data in Focus Group Research, *International Journal of Qualitative Methods* 8 (3) (2009) 1–21.
- [47] R.L. Scheaffer, W. Mendenhall, L. Ott, Elementary Survey Sampling, *Biometrics* 47 (Issue 2) (2006), <https://doi.org/10.2307/2532183>.
- [48] J.C. Gill, B.D. Malamud, Hazard interactions and interaction networks (cascades) within multi-hazard methodologies, *Earth System Dynamics* 7 (3) (2016) 659–679, <https://doi.org/10.5194/esd-7-659-2016>.
- [49] L. Jackering, T. Godecke, M. Wollni, Agriculture – nutrition linkages in farmers' communication, *The Journal of the International Association of Agricultural Economics* August (2019), <https://doi.org/10.1111/agec.12516>.
- [50] E.N. Muange, Social Networks, Technology Adoption and Technical Efficiency in Smallholder Agriculture: The Case of Cereal Growers in Central Tanzania (Issue December), 2015. <https://ediss.uni-goettingen.de/handle/11858/00-1735-0000-0022-5FA0-E>.
- [51] Gujarati, *Basic Econometrics* (Fourth Edn), The McGraw–Hill Companies, 2004.
- [52] J. Wang, Y. Deng, H. Diao, Market returns, external pressure, and safe pesticide practice: Moderation role of information acquisition, *International Journal of Environmental Research and Public Health* 15 (9) (2018), <https://doi.org/10.3390/ijerph15091829>.
- [53] V. Ruiz-Villanueva, S. Allen, M. Arora, N.K. Goel, M. Stoffel, Recent catastrophic landslide lake outburst floods in the Himalayan mountain range, *Progress in Physical Geography* 41 (1) (2017) 3–28, <https://doi.org/10.1177/0309133316658614>.
- [54] K. Mertens, L. Jacobs, J. Maes, C. Kabaseke, M. Maertens, J. Poesen, M. Kervyn, L. Vranken, The direct impact of landslides on household income in tropical regions: A case study from the Rwenzori Mountains in Uganda, *Science of the Total Environment* 550 (2016) 1032–1043, <https://doi.org/10.1016/j.scitotenv.2016.01.171>.
- [55] R.B. Kline, *Principles and Practice of Structural Equation Modeling*, The Guilford Press, New York London, 2011.
- [56] V. Singh, S.K. Sharma, Analyzing the moderating effects of respondent type and experience on the fuel efficiency improvement in air transport using structural equation modeling, *European Transport Research Review* 8 (2) (2016), <https://doi.org/10.1007/s12544-016-0199-3>.
- [57] C. Lee, O. Peters, C. Enders, A primer for the estimation of structural equation models in the presence of missing data: Maximum Likelihood Algorithms, *Journal of Targeting, Measurement and Analysis for Marketing* 11 (1) (2002) 81–95.
- [58] G.W. Cheung, R.S. Lau, Accuracy of Parameter Estimates and confidence intervals in Moderated Mediation Models: A Comparison of Regression and Latent Moderated Structural Equations, *Organizational Research Methods* 20 (4) (2017) 746–769, <https://doi.org/10.1177/1094428115595869>.
- [59] T.R. Duclos, W.V. DeLuca, D.I. King, Direct and indirect effects of climate on bird abundance along elevation gradients in the Northern Appalachian mountains, April, *Diversity and Distributions* (2019) 1670–1683, <https://doi.org/10.1111/ddi.12968>.
- [60] H. Liu, X. Luo, Understanding farmers' perceptions and behaviors towards farmland quality change in northeast China: A structural equation modeling approach, *Sustainability* 10 (9) (2018), <https://doi.org/10.3390/su10093345>.
- [61] Stata, *Stata Structural Equation Modeling Reference Manual Release, 17*, A Stata Press Publication (StataCorp LLC, College Station, Texas, 2015. <http://www.stata.com/manuals14/sem.pdf>.
- [62] P. Tarka, The comparison of estimation methods on the parameter estimates and fit indices in SEM model under 7-point Likert scale, *Archives of Data Science* 2 (1) (2017) 1–16, <https://doi.org/10.5445/KSP/1000058749/10>.
- [63] R.C. Tsai, Structural equation modeling of approval voting data, *Behavior Research Methods* 42 (3) (2010) 798–808, <https://doi.org/10.3758/BRM.42.3.798>.
- [64] M.W. Cheung, Implementing Restricted Maximum Likelihood Estimation in Structural Equation Models Teacher, s Corner, 2013, p. 5511, <https://doi.org/10.1080/10705511.2013.742404>.
- [65] W.H. Greene, *Econometric analysis* (fifth), Prentice Hall, Upper Saddle River, New Jersey, 2002, 07458.
- [66] S. Lukman, P.X. Bao, B. Kweku-Lugu, V.E. Arkorful, A. Latif, A. Gadabu, P. Charmaine-Kwade, I. Basiru, M.A. Sadiq, Diasporan students social entrepreneurship intention: The moderating role of institutional support, *Journal of Public Affairs* 21 (1) (2021), <https://doi.org/10.1002/pa.2108>.
- [67] S.T. Hannah, J.M. Schaubroeck, A.C. Peng, R.G. Lord, L.K. Trevino, S.W.J. Kozlowski, B.J. Avolio, N. Dimotakis, J. Doty, Joint Influences of Individual and Work unit abusive supervision on Ethical Intentions and Behaviors, *A Moderated Mediation Model* 98 (4) (2013) 579–592, <https://doi.org/10.1037/a0032809>.
- [68] L. Elite Research, Stats - Moderation, 2013. https://www.sheffield.ac.uk/polopoly_fs/1.8851721/file/90_Moderation_Mediation.pdf.
- [69] R.M. Baron, D.A. Kenny, The Moderator-Mediator Variable distinction in Social Psychological Research: conceptual, Strategic, and Statistical considerations, *J. Pers. Soc. Psychol.* 51 (6) (1986) 1173–1182, <https://doi.org/10.1037//0022-3514.51.6.1173>.
- [70] J. Sok, H. Hogeveen, A.R.W. Elbers, A.G.J.M.O. Lansink, Using farmers' attitude and social pressures to design voluntary Bluetongue vaccination strategies, *Preventive Veterinary Medicine* (2016), <https://doi.org/10.1016/j.prevetmed.2016.09.016>.
- [71] T.A. Brown, *Confirmatory Factor Analysis for Applied Research*, Second Edn, The Guilford Press, New York London, 2006.
- [72] L.J. Cronbach, On estimates of test reliability, *Journal of Educational Psychology* 34 (8) (1943) 485–494, <https://doi.org/10.1037/h0058608>.
- [73] L.J. Cronbach, Coefficient alpha and the internal structure of tests, *Psychometrika* 16 (3) (1951) 297–334, <https://doi.org/10.1007/BF02310555>.
- [74] P.N.C. Sanne, M. Wiese, The theory of planned behaviour and user engagement applied to Facebook advertising, *SA Journal of Information Management* 20 (1) (2018) 1–10, <https://doi.org/10.4102/sajim.v20i1.915>.
- [75] P. de Bérail, M. Guillon, C. Bungener, The relations between YouTube addiction, social anxiety and parasocial relationships with YouTubers: A moderated-mediation model based on a cognitive-behavioral framework, *Computers in Human Behavior* 99 (September 2018) (2019) 190–204, <https://doi.org/10.1016/j.chb.2019.05.007>.
- [76] X. Feng, L. Wang, Y. Yan, Q. Zhang, L. Sun, J. Chen, Y. Wu, The Sustainability of Knowledge-Sharing Behavior Based on the Theory of Planned Behavior in Q & A Social Network Community, 2021, Hindawi Complexity, 2021.
- [77] Y. Dwivedi, S. Schneberger, M.R. Wade, *Integrated Series in Information Systems*, 28, Springer, 2012.
- [78] A. Daxini, M. Ryan, C. O'Donoghue, A.P. Barnes, Understanding farmers' intentions to follow a nutrient management plan using the theory of planned behaviour, *Land Use Policy* 85 (November 2018) (2019) 428–437, <https://doi.org/10.1016/j.landusepol.2019.04.002>.
- [79] N. Arunrat, C. Wang, N. Pumijumnong, S. Sreenonchai, W. Cai, Farmers' intention and decision to adapt to climate change: A case study in the Yom and Nan basins, Phichit province of Thailand, *Journal of Cleaner Production* 143 (2017) 672–685, <https://doi.org/10.1016/j.jclepro.2016.12.058>.
- [80] Y. Huang, E. Lange, Y. Ma, Living With Floods and reconnecting To the Water – landscape Planning and Design for delta Plains, *Journal of Environmental Engineering and Landscape Management* 30 (1) (2022) 206–219, <https://doi.org/10.3846/jeelm.2022.16352>.
- [81] N.S. Podgornov, R.V. Davydov, D.K. Zotov, V.I. Antonov, V.I. Maslikov, E.I. Maslikova, A.N. Chusov, A.V. Cheremisin, Socio-ecological consequences during the construction of a multistage system of flood control facilities on side tributaries, *Journal of Physics: Conference Series* 1942 (1) (2021), <https://doi.org/10.1088/1742-6596/1942/1/012059>.

- [82] W. Liu, A. Sidhu, A. Beacom, T.W. Valente, Social Network Theory, Jon Wiley & Sons, Inc, 2017, <https://doi.org/10.1002/9781118783764.wbieme0092>.
- [83] J. Sekajugo, G. Kagoro-rugunda, R. Mutyebere, C. Kabaseke, E. Namara, Can citizen scientists provide a reliable geo- hydrological hazard inventory ? An analysis of biases , sensitivity and precision for the Rwenzori, Uganda, *Environmental Research Letters* 17 (4) (2022) 1–15.
- [84] R. Gempp, M. González-Carrasco, Peer relatedness, school satisfaction, and life satisfaction in Early adolescence: A Non-recursive Model, *Frontiers in Psychology* 12 (March) (2021) 1–9, <https://doi.org/10.3389/fpsyg.2021.641714>.